Model based Spike detection of Epileptic EEG data by using LabVIEW

Mr. V. Nageshwar[1]
Associate Professor
Department of EIE,
VNR VJIET
Hyderabad, Telangana, India

Mr. P. Prashanth Reddy[2]
Research scholar
Department of EIE,
VNR VJIET
Hyderabad, Telangana

Dr. Y. Padma sai[3]
Professor
Department of ECE,
VNR VJIET
Hyderabad, Telangana, India

Abstract: About 10 million people with epilepsy are there in India. Many people with active epilepsy do not receive appropriate treatment for their condition, Prior to treatment of seizure, its detection itself has been one of toughest tasks over decades this is because of its uncertainty. It takes one to either be a technician or an experienced doctor to analyse the EEG and say whether seizure exists or not. So we aim at providing an easily understandable tool to analyse the EEG signal especially to detect Seizure.

Accurate automatic spike detection is highly beneficial to clinical assessment of epileptic electroencephalogram (EEG) data. In this paper, a new three stage approach is proposed for elliptical spike detection. The project aims at the detection of seizures in EEG signal using Spike detection analysis.The real time EEG signal is been acquired from the Data set is processed and simulated to detect Seizure in the respective samples. Hence with the help of LabVIEW, a graphical programming language, a code based on algorithm namely spike detection method to detect seizure. This requires a minimal technical knowledge unlike orthodox way of analysing EEG.

Key Words: *LabVIEW, epilepsy; slow wave, spike detection, spike classification, nonlinear energy operator.*

i). Introduction:

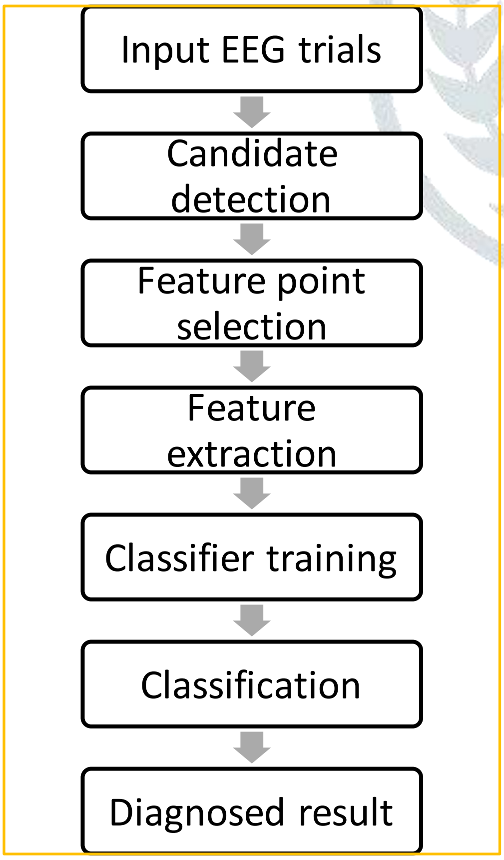
Epilepsy is a common brain disease. To monitor the functional disorders of the brain, the most popular way is to measure the electroencephalogram (EEG), which is a measurement of the electrical potentials produced by the brain. Diagnosis of epilepsy is usually based on the presence of typical epileptiform patterns, such as spikes and sharp waves, in the EEG. Visual scanning of EEG recordings for these patterns remains the most common approach, though it is very laborious and time-consuming. Furthermore, is agreement among neurologists concerning the same data may occur due to subjective differences. Therefore, to alleviate the drawbacks caused by subjective manual inspection, automatic detection of epileptiform patterns, based on objective criteria, would be of great benefit to clinical diagnosis and quantitative analysis.

Various automatic spike detection algorithms have been previously published. Algorithms are generally categorized into the following methods: template matching, mimetic analysis, power spectral analysis, wavelet analysis and artificial neural networks (ANNs). Features, obtained from mimetic, power spectral or wavelet analysis, are usually treated as inputs to ANNs. Many conventional methods adopting different classifiers together with single spike related features for spike classification were reported in. In clinical EEG data, it is often observed that a spike is followed by a slow wave. Both spikes and spikes with slow waves are regarded as positive epileptiform patterns by neurologists. Several papers have mentioned the existence of slow waves following the spike, but the slow wave was not utilized in the spike detection. In 2011, Ji's group proposed to use some features of slow waves in their spike detection algorithms. They used slow wave features (amplitude and duration) directly in some threshold rules to help in defining spike candidates and decreasing the false positives. Their experiments supported the fact that the slow waves did help in the detection of epileptic spikes.

Model-Based Spike Detection algorithm is used to classify the given signal into two classes that is either a signal containing the epilepsy, or a signal not containing an epilepsy. A real time signal is given to Model-Based Spike Detection VI, and a spikes are found at the place where the epilepsy is detected, thus, confirming a presence of epilepsy in the given signal. Algorithm was built and executed in LabVIEW.

ii). Materials:

Six scalp EEG data sheets from elliptical patients and three from normal subjects were used in this study.These datasets were anonymized and randomly selected from the EEG data bank. The EEG sensors were attached to the international 10–20 electrode system and EEGs were recorded.



EEG data was filtered by a 1–70 Hz band-pass filter and sampled at a rate of 250 Hz. Sixteen-channel EEGs (locations Fp1, Fp2, F3, F4, F7, F8, T3, T4, T5, T6, C3, C4, P3, P4, O1 and O2) from the recorded data were reviewed

EEG data sheet no.	Number of spikes	Number of spikes with slow waves
1	0	15
2	0	16
3	1	8
4	4	6
5	0	14
6	5	4

Table 1. *EEG data sheet*

iii). LabVIEW:

LabVIEW is a highly productive development environment for creating custom applications that interact with real-world data or signals in fields such as science and engineering. The net result of using a tool such as LabVIEW is that higher quality projects can be completed in less time with fewer people involved. This system extracts certain features from the data after pre-processing it to remove artefacts, and uses different signal processing techniques, and finally displays a graph of the same. It also allows for the results to be stored digitally, and printed if necessary. Thus, it satisfies, in part, the expectations from such a system.

iv). Methods:

The proposed system utilizes a three–stage approach for spike detection. Since an epileptic spike consists of two types of patterns (i.e., single spikes and spikes with slow waves), we adopt threshold and time frequency to detect all possible spike candidates using the features of the newly proposed spike model.

Figure 1 shows the flowchart of the proposed method. The candidate detection, feature point selection, feature extraction and classification procedures are detailed below

Fig *1. Flow chart of Process*

Peak detection:

Peak detection is one of the most important time-domain functions performed in signal monitoring. Peak detection is the process of finding the locations and amplitudes of local maxima and minima in a signal that satisfies certain properties. These properties can be simple or complex. For example, requiring that a peak exceeds a certain threshold value is a simple property. However, requiring that a peak's shape resembles that of a prototype peak is a complex property.

Feature extraction and selection:

Each segment of an EEG signal may be represented by computed features (usually more than one) or by a combination of computed features. This part of the EEG processing process is crucial, because it provides the ability to distinguish between different classes. It thus directly affects the accuracy of the final classification. The set of features that is used may include statistical features, frequency features computed for typical and extended EEG bands, features obtained by interval or period analysis, entropy-based features, features extracted after application of the Discrete Wavelet Transform (DWT), etc. With feature extraction from EEG several hundreds of features can be acquired. This may be burdensome for further processing. The dimensionality of the feature space can be reduced by selecting subsets of features. There are various strategies and criteria for searching useful subsets of relevant features from the initial set of features.In other words, feature selection considered to be successful if the dimensionality of the data is reduced and the classification accuracy improves or remains the same.

Imagine a study evaluating a new test that screens people for a disease. Each person taking the test either has or does not have the disease. The test outcome can be positive (classifying the person as having the disease) or negative (classifying the person as not having the disease). The test results for each subject may or may not match the subject's actual status.

Fig*.2*Feature points on model

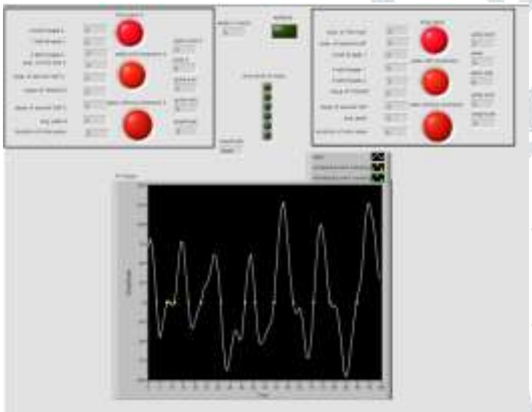
Accurate automatic spike detection is highly beneficial to clinical assessment of epileptic electroencephalogram (EEG) data. Diagnosis of epilepsy is usually based on the presence of typical epileptiform patterns, such as spikes and sharp waves, in the EEG. Visual scanning of EEG recordings for these patterns remains the most common approach, though it is very laborious and time-consuming. Furthermore, disagreement among neurologists concerning the same data may occur due to subjective differences. Therefore, to alleviate the drawbacks caused by subjective manual inspection, automatic detection of epileptiform patterns, based on objective criteria, would be of great benefit to clinical diagnosis and quantitative analysis. A new two-stage approach is proposed for epileptic spike detection. First, the threshold detector is adopted to detect all possible spike candidates, then a newly proposed spike model with slow wave features is applied to these candidates for spike classification

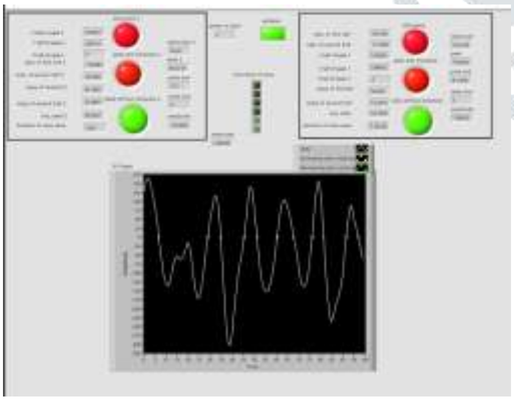
v). Results and discussion:

Candidate Detection: In the following experiments, each 10 second EEG trial contained many signal fluctuations where only 1 or 2 spike-like short duration patterns (in tens of milliseconds) could be detected. The remaining EEG fluctuations were regarded as background signals in spike However, the number of detected candidates is related to the selected threshold T from the candidate detection procedure. The lower the threshold T, the more spike candidates would be acquired resulting in more computation in the subsequent processing. On the other hand, the higher the threshold T, the less the number of candidates would be selected and the higher the chance to harbour false negatives. Threshold T was set to 140 µv empirically in all our experiments.

This section evaluates the performance of spike classification. Based on the confusion matrix, TP, FP, TN and FN denote the number of true positives, false positives, true negatives and false negatives, respectively. The accuracy of the classification was calculated by the following equation:

The classification was calculated by the following equation:





$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

$$Accuracy = \frac{8+5}{8+1+5+0}$$

$$= \frac{13}{14} * 100\%$$

$$= 92.85\%$$

If the samples are not large enough or are unevenly distributed in the training and testing datasets, system performance might be negatively affected. In order to reduce this effect, four-fold cross-validation process was employed. The four-fold was selected based on the available number of trials. Too large a fold number which makes each fold have too small a number of trials will make the results less statistically meaningful. The experimental dataset was randomly divided into four groups. Each of the four groups alternately served as the testing dataset with the other three groups combined to be training dataset. The testing results from the four groups are summed up to obtain the testing statistics of a four-fold test instance. This four-fold test process was repeated ten times to obtain the final statistics for each classification experiment.Statistical sensitivity and specificity were computed for the performance of the classification system. Sensitivity reflected the ability of detecting spikes, while specificity evaluated the ability of discriminating non-spikes. The quantities were defined as:

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Sensitivity = \frac{8}{8+0}$$

$$= 100\%$$

Using the proposed spike method the results for training reached 100%.

A)*.Healthy Signal (Good Signal)*

B). *Peak with Slow-wave*

C). *Peak without Slow-wave*

vi). Conclusion

- Epilepsy is detected using Model-Based Spike Detection algorithm.
- Model-Based Spike Detection is one of the best algorithm for the classification of complex data.
- By taking 14 samples and training the Model-Based Spike Detection module, the accuracy to detect the epilepsy is increased. In the same way, a huge number of samples, for example-200, can be taken to detect the epilepsy
- The abnormal waveform is easily seen in the time frequency analysis, and thus, a seizure is detected.

vii). Future Scope for the project

The problem associated with the detection of seizure is that there are many methods that approximated the occurrence of the seizure, but cannot give out a perfect prediction, because of its capricious nature. We can use these techniques to detect a seizure from a given EEG signal. Apart from this, the Model-Based Spike Detection algorithm in LabVIEW can be used for other graphical analysis like image retrieval. As the toolkits in LabVIEW keep getting updated, the Model-Based Spike Detection algorithm simultaneously gets updated, increasing the efficiency and the accuracy of the detection of the seizures.

viii). References:

1. Löfhede, J.; Seoane, F.; Thordstein, M. Textile electrodes for EEG recording—A pilot study. Sensors 2012, 12, 16907–16919
2. Ji, Z.; Sugi, T.; Goto, S.; Wang, X.; Ikeda, A.; Nagamine, T.; Shibasaki, H.; Nakamura, M. An automatic spike detection system based on elimination of false positives using the large-area context in the scalp EEG. IEEE Trans. Biomed. Eng. 2011, 58, 2478–2488.
3. Halford, J.J. Computerized epileptiform transient detection in the scalp electroencephalogram: Obstacles to progress and the example of computerized ECG interpretation. Clin. Neurophysiol. 2009, 120, 1909–1915.
4. Indiradevi, K.P.; Elias, E.; Sathidevi, P.S.; Dinesh, N.S.; Radhakrishnan, K. A multi-level wavelet approach for automatic detection of epileptic spikes in the electroencephalogram. Comput. Biol. Med. 2008, 38, 805–816.
5. Tzallas, A.T.; Karvelis, P.S.; Katsis, C.D.; Fotiadis, D.I.; Giannopoulos, S.; Konitsiotis, S. A method for classification of transient events in EEG recordings: application to epilepsy diagnosis. Methods Inf. Med. 2006, 45, 610–621.
6. Exarchos, T.P.; Tzallas, A.T.; Fotiadis, D.I.; Konitsiotis, S.; Giannopoulos, S. EEG transient event detection and classification using association rules. IEEE Trans. Inf. Technol. Biomed. 2006, 10, 451–457.
7. Acir, N.; Oztura, I.; Kuntalp, M.; Baklan, B.; Guzelis, C. Automatic detection of epileptiform events in EEG by a three-stage procedure based on artificial neural networks. IEEE Trans. Biomed. Eng. 2005, 52, 30–40.
8. Güler, I.; Übeyli, E.D. Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients. J. Neurosci. Methods 2005, 148, 113–121.
9. Adjouadi, M.; Cabrerizo, M.; Ayala, M.; Sanchez, D.; Yaylali, I.; Jayakar, P.; Barreto, A. A new mathematical approach based on orthogonal operators for the detection of interictal spikes in epileptogenic data. Biomed. Sci. Instrum. 2004, 40, 175–180.
10. Wilson, S.B.; Emerson, R. Spike detection: A review and comparison of algorithms. Clin. Neurophysiol. 2002, 113, 1873–1881.
11. Hellmann, G. Multifold features determine linear equation for automatic spike detection applying neural nin interictal ECoG. Clin. Neurophysiol. 1999, 110, 887–894.
12. Ktonas, P.Y. Automated Spike and Sharp Wave (SSW) Detection. In Methods of Analysis of Brain Electrical and Magnetic Signals (Handbook of Electroencephalography and Clinical Neurophysiology, Rev Series 1); Gevins, A.S., Remond, A., Eds.; Elsevier:

Amsterdam, The Netherlands, 1987; pp. 211–241.
13. Gotman, J.; Gloor, P. Automatic recognition and quantification of interictal epileptic activity in the human scalp EEG. Electroencephalogr. Clin. Neurophysiol. 1976, 41, 513–529.
14. Chatrian, G.E.; Bergamini, L.; Dondey, M.; Klass, D.W.; Lennox-Buchthal, M.; Petersen, I. A glossary of terms most commonly used by clinical electroencephalographers. Electroencephalogr. Clin. Neurophysiol. 1974, 37, 538–548.