CATEGORIZATION OF EEG DEMONSTRATES FOR IDENTIFICATION OF EPILEPTIC SEIZURES BEARING ON WAVELETS AND NUMERICAL PATTERN CLASSIFICATION

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ABSTRACT:

Detection of epilepsy relies heavily on the electroencephalogram (EEG). An epileptic patient's long-term EEG recordings contain an enormous amount of EEG data. As a result, detecting epileptic activity is a difficult task that necessitates an in-depth review of the full EEG data set by a professional. Using wavelet transform and statistical pattern recognition, this work describes an automated classification of EEG signals for the identification of seizures. Feature extraction based on wavelet transform, feature space dimension reduction with scatter matrices, and classification with quadratic classifiers are the three primary stages of the decision-making process. This methodology was applied to EEG data sets from three subject categories: (a) healthy volunteers, (b) epileptics during a seizure-free time, and (c) epileptics during a seizure. Overall, we were able to attain a classification accuracy of 99 percent. According to the study results, a proposed algorithm has the ability to classify EEG signals and detect epileptic episodes. This could help improve the diagnosis of epilepsy.

Keywords: Diagnosis of epilepsy; Detection of convulsions; Scatter matrices; Dimension reduction; Quadratic classifiers

INTRODUCTION:

Nearly 60 million individuals worldwide are estimated to suffer from epilepsy, according to the World Health Organization. As many as one in a hundred people will suffer from a seizure at some point in their lives. People who suffer from epilepsy experience seizures that are frequent and unexpected, which can put them in danger and even endanger their lives[2]. In the EEG signal, which represents the electrical activity of the brain, there occurs a momentary and unexpected electrical disturbance of the brain and excessive neuronal discharge. When it comes to assessing the brain's health and detecting epileptic seizures, EEG is the most commonly used signal. This is critical for a thorough diagnosis of epilepsy.

Patients' EEG data is laborious and time-consuming to scan for signs of epileptic seizures via visual scanning. EEG recordings must be analysed in their entirety by an expert to detect epileptic activity. Epilepsy diagnosis and long-term patient monitoring and treatment would be vastly improved with an automated categorization and detection system that could be relied upon to provide objective results. An antiepileptic pharmacological treatment that may generate cognitive or other neurological side effects could, for example, be reduced to a focused short-acting intervention[3]. In order to properly evaluate and treat neurological illnesses such as epilepsy, there is a high demand for the creation such automated systems due to the large volumes and rising use of long-term EEG recordings. The expert's ability to misinterpret the data and come up with an incorrect conclusion would also be reduced[4,5].

There have been a slew of new algorithms for classifying and detecting seizures in EEG signals that have appeared in recent years. For example, Gotman's computerised system can detect a wide range of seizures, while Qu and Gotman's nearest-neighbor classifier on EEG data derived in both time and frequency domains may detect epileptic seizures. For epileptic seizure onset prediction from intracranial epileptic EEG recordings, Gigola et al.[8] used a method based on the evolution of accumulated energy using wavelet analysis, while Adeli et al.[9], Guler et al.[10], and Ubeyli [11] discussed the potential of nonlinear time series analysis in seizure detection.

Several researchers [11–13] have proposed artificial neural network-based detection systems for epilepsy diagnosis. According to Weng and Khorasani[14], an adaptive structured neural network is fed with the Gotman and Wang[15] properties of average EEG amplitude and duration as well as variation coecients, dominating frequencies, and average power spectra. Learning vector quantization networks can be trained using raw EEG signals, as demonstrated by Pradhan and colleagues[16]. Two EEG properties, relative spike amplitude and spike rhythmicity have been employed as inputs for the aim of identifying seizures in a new neural network model presented by Nigam and Graupe [17].

Uses back propagation neural network with periodogram and autoregressive (AR) characteristics as inputs for automated detection of epileptic seizures, according to Kiymik et al. [18]. Wavelet analysis, radial basis function, and a Levenberg–Marquardt backpropagation neural network were used by Ghosh-Dastidar et al. to develop a classification approach. Classifying EEG signals and seizures using wavelet analysis and a combination of specialists was done by Srinivasan et al. [20] using an approach based on approximation entropy as an input to an artificial neural network classifier.

Most present approaches have low accuracy, a high proportion of false alarms, and missed detections since the mechanisms behind the problem are so little understood[22]. Most EEG analysis-based algorithms are based on a small number of datasets, which often show acceptable accuracy for selected EEG segments but are not strong enough to adjust to EEG variability commonly observed in a hospital setting[20]. These studies included a greater number of EEG data sets from three different types of participants: healthy individuals (normal EEG), epileptic individuals during a seizure-free time (interictal EEG), and epileptic individuals experiencing a seizure itself (periictal EEG) (ictal EEG). Using a three-group classification problem, the EEG signal classification and seizure detection problem was analysed. One can utilise an automated method that is capable of properly separating between normal and ictal EEG data to determine if a person has epilepsy, while another is capable of detecting seizures in the clinical situation. In order to effectively classify all three categories, the classification system must be able to handle EEG signal fluctuations across different mental states and people. By identifying combinations of all extracted features that promote inter-class separation, and classifiers that can effectively classify all three groups of EEG signals based on a restricted feature space, the classification accuracy can be improved. It was found that the algorithm may be used in an automated epilepsy diagnosis system after it was tested using real EEG data.

MATERIALS AND METHODS:

Materials:

Subsets of normal and epileptic EEG data made accessible by Dr. Ralph Andrzejak of the Epilepsy Center at the University of Bonn were utilised. Patients with epilepsy during a period without seizures had their interictal EEG data evaluated, while patients with epilepsy during a seizure episode had their seizure-related ictal (epileptic) EEG data examined. These three categories of patients' EEG data were examined. 100 single-channel EEG segments were recorded with a 128-channel amplifier setup at 173.61 Hz for a total of 23.6 s in length for each of the data sets. After a visual assessment for artefacts (e.g. due to muscular activity or eye movement), these segments were selected and cut from the continuous multi-channel EEG recordings. The segments also required to meet a stationarity condition, which was detailed in detail in Andrzejak et al. [23]. Using a consistent electrode placement technique, the first set of EEG data relating to healthy people was obtained from surface EEG recordings made while the subjects were calm and awake. The second and third data sets were acquired from intracranial EEG recordings made during presurgical diagnosis from five distinct epileptic participants during seizure-free and seizure intervals, respectively.

Temporal lobe epilepsy with the epileptogenic foci in hippocampal formations was diagnosed. Figure 1[23] depicts a schematic of how intracranial electrodes are to be placed. They implanted both depth electrodes and strip electrodes symmetrically into the hippocampal formations, which are located in the neocortex's anterior and posterior regions. All of the recording sites that showed ictal activity were used to select the EEG segments. A total of 300 EEG data segments were generated by treating each EEG segment as an unique EEG signal.

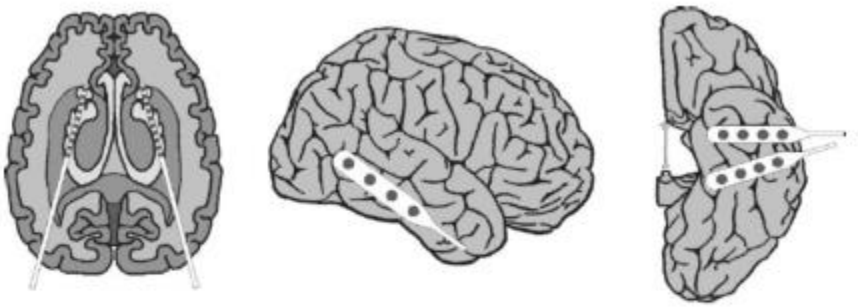
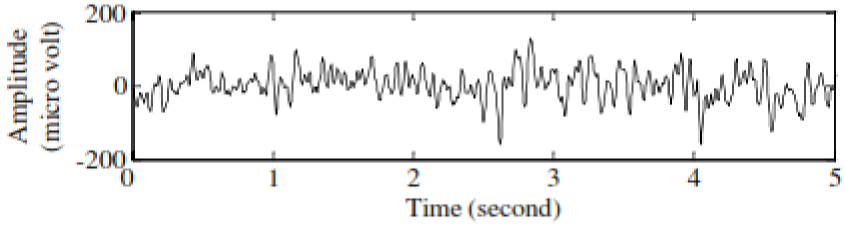
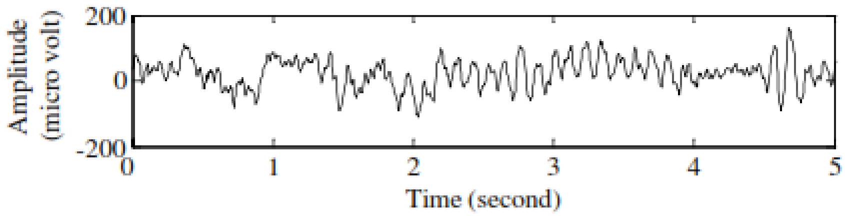


Figure 1 Implanted electrodes in the brain

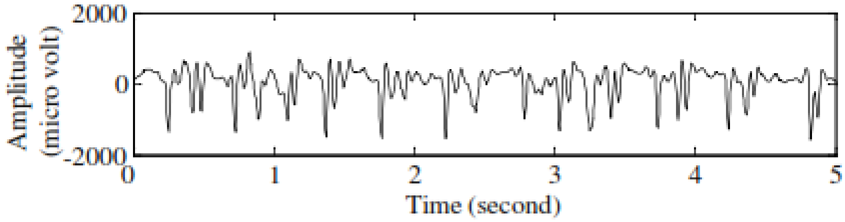
The first five seconds of all three EEG data segments are displayed in Fig. 2 as an example. Only transient waveforms, such as isolated spikes, spike trains, sharp waves, or spike wave complexes, can be found in interictal EEG data; however, continuous discharges of polymorphic waveforms, spike and sharp wave complexes, rhythmic hypersynchrony, or electrocerebral inactivity, observed over a duration longer than the average duration of these abnormalities during interictal perfusion, can be found in ictal EEG data.



(A)



(B)



(C)

Figure 2 Segments of EEG data: (A) Normal, (B) Interictal and (C) Ictal

It is common practise to study the EEG signal in terms of the following five wide spectral subbands: delta (0–4Hz), theta (4–8Hz), alpha (8–16 Hz), beta (16–32 Hz), and gamma waves (32–64 Hz). As a result of aberrant brain states like epilepsy, the EEG signal energy shifts from lower frequency bands to higher frequency bands before and during a seizure. It is possible that alterations in the EEG signal that are not readily apparent in the full-spectrum signal can be increased when each of these five frequency sub-bands is analysed separately because they provide more accurate information about the neuronal processes at the root of the problem. This study's key concept was that. The wavelet decomposition of the full-spectrum EEG signal, as well as the inverse wavelet transform, were used to extract most of the information from each sub band. For example, in Fig. 3, where only theta sub-bands are shown, the contrast between normal and interictal EEG data is more obvious than in Fig. 2, where the identical signals but entire spectrum are provided. In contrast, the greater amplitudes of ictal EEG data make them easier to discern.

Methods:

Wavelet transforms and statistical pattern recognition are used to classify EEG signals for the detection of epileptic episodes. A wavelet transform of the EEG data is used to derive a collection of features, including energy, entropy and standard deviation of the wavelet coefficients and the EEG signal in various frequency bands of clinical interest, as the initial step in this procedure. Scatter matrices are used to reduce the dimension of the feature space in the second stage. Classifiers that are able to discriminate all three EEG signal groupings from each other are then developed, including two quadratic ones. In Fig. 4, you can see the algorithm's whole structure.

Wavelets transform:

When diagnosing serious neurological conditions such as epilepsy, abnormalities in EEG data are too subtle to be discovered by standard techniques, which typically turn primarily qualitative diagnostic criteria into a more objective quantitative signal feature classification problem. The autocorrelation function, time domain features, frequency domain features, time frequency analysis, nonlinear time series analysis, and the wavelet transform have all been used to analyse EEG signals in order to detect epileptic convulsions. Wavelet transform, on the other hand, has emerged as the best method for obtaining EEG signal characteristics. As a result, EEG signals were subjected to the wavelet transform in order to extract useful information.

There are several uses for the wavelet transform, which is a linear time-frequency transform, including investigation of transient or non-stationary phenomena, as well as the reduction of noise. A class of functions, it has the capacity to localise information in both time and frequency. It is because of this that the wavelet transform has been frequently used in biological signal processing.

Decomposing a given signal x(t) into increasingly finer details using two sets of basis functions, wavelets and scaling functions, is known as discrete wavelet analysis.

$$x(t) = \sum_{k} 2^{j_0/2} a_{j_0}(k) \varphi(2^{j_0} t - k)$$
$$+ \sum_{j=j_0}^{\infty} \sum_{k} 2^{j/2} d_j(k) \psi(2^j t - k), \qquad (1)$$

$$a_j(k) = \int_{-\infty}^{\infty} 2^{j/2} x(t) \varphi(2^j t - k) dt, \qquad (2)$$

$$d_j(k) = \int_{-\infty}^{\infty} 2^{j/2} x(t) \psi(2^j t - k) dt, \qquad (3)$$

The wavelet approximation and detail coefficients are denoted by aj(k) and dj(k), respectively. The DWT divides the frequency axis into dyadic intervals when the bandwidth length drops exponentially at lower frequencies. DWT is generalised into the wavelet packet (WP) transform, which decomposes data in both directions (lower and higher frequencies). The general decomposition is more flexible than the discrete wavelet decomposition in signal analysis. Decomposition levels (scales) and frequency bands are used to identify each node in the WP tree. An efficient signal analysis method is provided by the wavelet transform's adaptive time-scale representation and decomposition of a signal into different frequency sub-bands[36]. It is possible to rebuild the signal and study its time-domain characteristics in each of the privy-derived subbands using wavelet coefficients generated following a wavelet transform.

Reduction of feature space:

The reduction matrix A can be determined in a number of distinct ways utilising various methods. Among these, the Karhunen–Loeve Expansion method[38], which, depending on the field of application, is sometimes known as principal component analysis, is the most frequently used (PCA). By analysing a covariance matrix, the objective of these methods is to discover the direction in which the random vector's scattering is highest. It is thought that this direction is the most informative and that, in the case of dimension reduction, it should be maintained because it conveys the most information. Nonetheless, such an approach is not always suitable for certain applications, such as the one being presented here. Figure 5 depicts the instances of a random two-dimensional vector. Based on the obtained eigenvectors and eigenvalues, the Karhunen–Loeve Expansion approach would determine the principal components z 1 and z. Since the eigenvalue that corresponds to the component z 2 is greater than the corresponding value of the component z 1, the dimension of the component z2 would be sacrificed and z1 would be kept following dimension reduction.

Nonetheless, the samples depicted in Figure 5 form two clusters that represent measurement data collected under different settings and belong to two distinct classes. If dimension reduction is merely a part of a broader process whose objective is the ultimate classification of measurements, then dimension reduction must address the separability of the categories that result from reduction. Figure 5 demonstrates unmistakably that it is preferable to retain another principal component, z, even though its eigenvalue is somewhat lower, because the projection of the original vectors onto the axis z2 will result in no overlap of matching probability density functions. In this manner, it is possible to accomplish a good categorization even in a little space.

$$M_k = E\{Z^{(k)}\},$$
$$\Sigma_k = E\{(Z^{(k)} - M_k)(Z^{(k)} - M_k)^T\}, \qquad (4)$$

Where E is the expectation operator in mathematics. In reality, however, because the related joint probability density functions are typically unknown, these mathematical expectations are frequently estimated by sample estimation.

$$M_k \approx \frac{1}{N_k} \sum_{j=1}^{N_k} Z_j^{(k)};$$

$$\Sigma_k \approx \frac{1}{N_k} \sum_{j=1}^{N_k} (Z_j^{(k)} - M_k)(Z_j^{(k)} - M_k)^T. \qquad (5)$$

It is also feasible to predict a priori probabilities of specific classes occurring within the data set.

$$P_k \approx \frac{N_k}{N}, \quad k = 1, \ldots, c. \qquad (6)$$

On the basis of these estimates, the scatter matrices inside class S w and between classes Sb are created as follows:

$$S_w = \sum_{k=1}^{c} P_k \Sigma_k;$$

$$S_b = \sum_{k=1}^{c} P_k (M_k - M_0)(M_k - M_0)^T;$$

$$M_0 = \sum_{k=1}^{c} P_k M_k. \qquad (7)$$

Within statistical discriminant analysis, within-class and between-class scatter matrices are utilised to determine class separability requirements. A within-class scatter matrix represents the scatter of samples around their respective class anticipated vectors, whereas a between-class scatter matrix represents the scatter of expected vectors around the mixed mean. The components of the within-class matrix should be as tiny as possible, whereas the elements of the between-class matrix should be as large as possible, if the members of various classes are distinguishable and no mixing occurs. There are various ways to satisfy these two needs. In this study, the following criterion is adopted:

$$J_1 = \mathrm{tr}\{S_2^{-1} S_1\}, \qquad (8)$$

$$A = [\Psi_1, \Psi_2, \ldots, \Psi_m], \qquad (9)$$

$$(S_2^{-1} S_1)\Psi_i = \lambda_i \Psi_i, \quad i = 1, \ldots, m \qquad (10)$$

$$l(m) = \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{n} \lambda_i} 100\%. \qquad (11)$$

An index of informativity could be used for l(m), given its importance. It is defined that the informativity index spans from 0% for m1/4 n to 100% for m1/4n. Using this index, it is possible to measure the amount to which information was saved after a dimension reduction. Dimension reduction outcomes with an informativity index more than or equal to 85% are generally considered satisfactory, as was the case in this instance.

CONCLUSIONS:

EEG data categorization was given in this study using a wavelet transform and statistical pattern recognition-based method that can objectively determine the type of EEG data processed and consequently a patient's brain state. The algorithm's main advantages include: (a) the ability of the algorithm to run robustly in a clinical setting with noisy EEG; (b) feature extractions with highly meaningful wavelet transform because hidden EEG information can be revealed and the noise effort reduced as certain data under some scales are omitted; (c) simplicity and low computational cost guaranteeing real clinical application; (d) very good sensitivity and specificity as well as an overall clas This means that the suggested approach is applicable in clinical settings for the classification of EEG signals and the detection of seizures.

Additional improvements can be made to the suggested algorithm, despite the overall classification accuracy being relatively good. Nonlinear series analysis (i.e., chaos analysis) of EEG data can be used to add extra features to the feature vector. Choosing more advanced pattern recognition algorithms results in a more complicated but also more accurate classification procedure. This is the other option. In addition, long-term continuous EEG recordings should be used to test the algorithm's ability to detect online seizures, as well as other EEG changes (e.g., those generated by cognitive tasks).

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