Reliable Epileptic Seizure Detection Using an Improved Wavelet Neural Network

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Abstract. Electroencephalogram (EEG) signals analysis is indispensable in epilepsy diagnosis as it offers valuable insights for locating the abnormal distortions in the brain wave. However, visual interpretation of the massive amount of EEG signals is time-consuming, and there is often inconsistent judgment between the experts. Thus, a reliable seizure detection system is highly sought after. A novel approach for epileptic seizure detection is proposed in this paper, where the statistical features extracted from the discrete wavelet transform are used in conjunction with an improved wavelet neural network in order to identify the occurrence of seizures. Experimental simulations were carried out on a well-known publicly available dataset, which was kindly provided by Ralph Andrzejak from the Epilepsy center in Bonn, Germany. The obtained high prediction accuracy, sensitivity and specificity demonstrated the feasibility of the proposed seizure detection scheme.

Keywords: Epileptic seizure detection, fuzzy *C*-means clustering, *K*-means clustering, type-2 fuzzy *C*-means clustering, wavelet neural networks.

1 Introduction

Since its first inception reported by German neuropsychiatrist Hans Berger in the year 1924, the electroencephalogram (EEG) signals, which record the electrical activity in the brain, have emerged as an essential alternative in diagnosing neurological disorders. By analyzing the EEG recordings, inherent information from different physiological states of the brain can be extracted, which are extremely crucial for the epileptic seizure detection since the occurrence of seizure exhibits clear transient abnormalities in the EEG signals. Thus, a warning signal can be initiated in time to avoid any unwanted seizure related accidents and injuries, upon detecting an impending seizure attack.

While vital as a ubiquitous tool which supports general diagnostic of epilepsy, the clinical implementation of EEG is constrained due to the challenges of: (i) Available therapies require long term continuous monitoring of EEG signals. The generated massive amounts of EEG recordings have to be painstakingly scanned and analyzed visually by neurophysiologists, which is a tedious and time-consuming task. (ii) There often is disagreement among different physicians during the analysis of ictal signals [19]. Undoubtedly, an automated diagnostic system that is capable of distinguishing the transient patterns of epileptiform activity from the EEG signals with reliable precision is of great significance.

Various efforts have been devoted in the literature in this regard. Generally speaking, a typical epileptic seizure detection process consists of two stages wherein, the inherent information that characterizes the different states of brain electrical activity are first derived from the EEG recordings using some feature extraction techniques, and subsequently, a chosen expert system is trained based on the obtained features. The discrete wavelet transform (DWT) has gained practical interest in extracting the valuable information embedded on the EEG signals due to its ability in capturing precise frequency information at low frequency bands and time information at high frequency bands [4], [9], [22], [25]. EEG signals are non-stationary in nature, and they contain high frequency information with short time period and low frequency information with long time period [18]. Therefore, by analyzing the biomedical signals at different time and frequency resolutions, DWT is able to preprocess the biomedical signals efficiently in the feature extraction stage.

In the second stage of the seizure detection scheme, a great deal of different artificial neural networks (ANNs) based expert systems have been utilized extensively in the emerging field of epilepsy diagnosis. For instance, the multilayer perceptrons, radial basis function neural networks, support vector machines, probabilistic neural networks, and recurrent neural networks are some of the models that have been previously reported in literature [5], [12], [14], [19], [22]. ANNs are powerful mathematical models that are inspired from their biological counterparts - the biological neural networks, which concern on how the interconnecting neurons process a massive amount of information at any given time. The utilization of ANNs in the seizure detection study is appropriate in nature, due to their capability of finding the underlying relationship between rapid variations in the EEG recordings, in addition to having the characteristics of fault tolerance, massive parallel processing ability, and adaptive learning capability.

The objective of this paper is to present a novel scheme based on an improved WNNs for the optimal classification of epileptic seizures in EEG recordings. The normal as well as the epileptic EEG signals were first pre-processed using the DWT wherein, the signals were decomposed into several frequency subbands. Subsequently, a set of statistical features were extracted from each frequency subband, and was used as a feature set to train a wavelet neural networks (WNNs) based classifier. It is worth mentioning that the feature selection of EEG signals using DWT and epileptic seizure detection with ANNs are well-accepted methodologies by medical experts [6-7].

The paper is organized as follows. In Section 2, the clinical data used in this study is first presented, followed by the feature extraction method based on the DWT. The implementation of the improved WNNs is next described in Section 3. In Section 4, the effectiveness of the proposed WNNs in epileptic seizure detection is presented and finally, conclusions are drawn in Section 5.

2 Materials and Methods

The flow of the methodology used in this study is depicted in the block diagram in Fig. 1, which will be discussed in detail in the following sections.

2.1 Clinical data selection

The EEG signals used in this study were acquired from a publicly available benchmark dataset [2]. The dataset is divided into five sets, labeled set A until E. Each set of the data consists of 100 segments, with each segment being a time series with 4097 data points. Each segment was recorded for 23.6 s at a sampling rate of 173.61 Hz. Each of the five sets was recorded under different circumstances. Both sets A and B were recorded from healthy subjects, with set A recorded with their eyes open whereas set B with their eyes closed. On the other hand, sets C until E were obtained from epileptic patients. Set C and D were recorded during seizure free period, where set C was recorded from the hippocampal formation of the opposite hemisphere of the brain, whereas set D was obtained from within the epileptogenic zone. The last data set, set E, contains ictal data that were recorded when the patients were experiencing seizure. In other words, the first four sets of data, sets A until D, are normal EEG signals, while set E represents epileptic EEG signals.

2.2 Discrete wavelet transform for feature extraction

DWT offers a more flexible time-frequency window function, which narrows when observing high frequency information and widens when analyzing low frequency resolution. It is implemented by decomposing the signal into coarse approximation and detail information by using successive low-pass and high-pass filtering, which is illustrated in Fig. 2.

As shown in this figure, a sample signal $x(n)$, is passed through the low-pass filter G_0 and high-pass filter H_0 simultaneously until the desired level of decomposition is reached. The low-pass filter produces coarse approximation coefficients $a(n)$, whereas the high-pass filter outputs the detail coefficients $d(n)$. The size of the approximation coefficients and detail coefficients decreases by a factor of 2 at each successive decomposition.

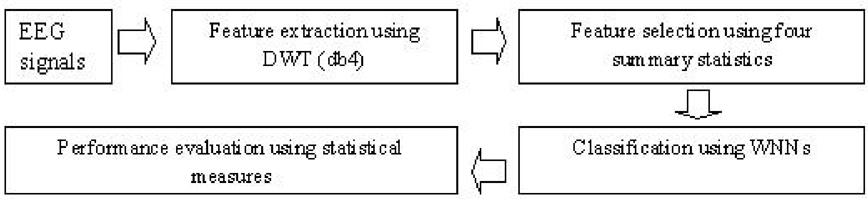

Fig. 1. Block diagram for the proposed seizure detection scheme.

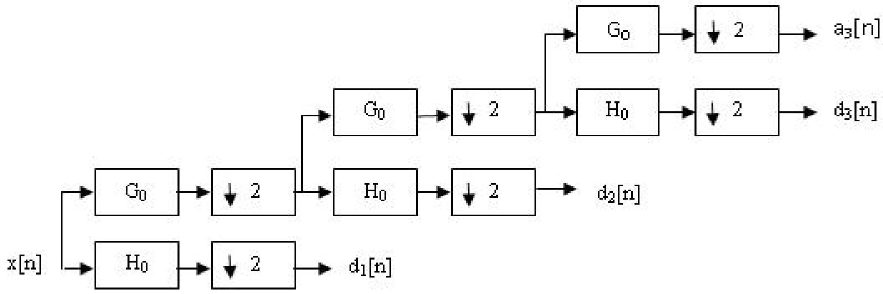

Fig. 2. A three-level wavelet decomposition tree.

Selecting the appropriate number of decomposition level is important for DWT. For the EEG signal analysis, the number of decomposition levels can be determined directly, based on their dominant frequency components. The number of levels is chosen in such a way that those parts of the signals which correlate well with the frequencies required for the classification of EEG signals are retained in the wavelet coefficients [17]. Since the clinical data used were sampled at 173.61Hz, the DWT using Daubechies wavelet of order 4 (db4), with four decomposition levels is chosen, as suggested in [21]. The db4 is suitable to be used as wavelets of lower order are too coarse to represent the EEG signals, while wavelets of higher order oscillate too wildly [1]. The four-level wavelet decomposition process will yield a total of five groups of wavelet coefficients, each corresponds to their respective frequency. They are d_1(43.4-86.8Hz), d_2(21.7-43.4Hz), d_3(10.8-21.7Hz), d_4(5.4-10.8Hz), and a_4(0-5.4Hz), which correlate with the EEG spectrum that fall within four frequency bands of: delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz) and beta (13-22Hz).

Subsequently, the statistical features of these decomposition coefficients are extracted, which are:

1. The 90th percentile of the absolute values of the wavelet coefficients
2. The 10th percentile of the absolute values of the wavelet coefficients
3. The mean of the absolute values of the wavelet coefficients
4. The standard deviation of the wavelet coefficients.

It is worth mentioning that instead of the usual extrema (maximum and minimum of the wavelet coefficient), the percentiles are selected in this case in order to eliminate the possible outliers [11]. At the end of the feature extraction stage, a feature vector of length 20 is formed for each EEG signal.

3 Classification using an improved wavelet neural networks

WNNs are feedforward neural networks with three layers – the input layer, the hidden layer, and the output layer [26] . As the name suggests, the input layer receives input values and transmits them to the single hidden layer. The hidden nodes consist of continuous wavelet functions, such as Gaussian wavelet, Mexican Hat wavelet, or Morlet wavelet, which perform the nonlinear mapping. The product from this hidden layer will then be sent to the final output layer.

Mathematically, a typical WNN is modeled by the following equation:

$$y(\mathbf{x}) = \sum_{i=1}^{p} w_{ij}\psi\left(\frac{\mathbf{x}-\mathbf{t}_i}{d}\right) + \mathbf{b}, \tag{1}$$

where y is the desired output, $\mathbf{x} \in \mathbb{R}^m$ is the input vector, p is the number of hidden neurons, w_{ij} is the weight matrix whose values will be adjusted iteratively during the training phase in order to minimize the error goal, ψ is the wavelet activation function, $\mathbf{t}$ is the translation vector, d is the dilation parameter, and $\mathbf{b}$ is the column matrix that contains the bias terms. The network structure is illustrated in Fig. 3.

The WNNs are distinct from those of other ANNs in the sense that [26]:

- WNNs show relatively faster learning speed owing to the constitution of the fast-decaying localized wavelet activation functions in the hidden layer.
- WNNs preserve the universal approximation property, and they are guaranteed to converge with sufficient training.
- WNNs establish an explicit link between the neural network coefficients and the wavelet transform.
- WNNs achieve the same quality of approximation with a network of reduced size.

Designing a WNN requires the researchers to focus particular attention on several areas. First, a suitable learning algorithm is vital in adjusting the weights between the hidden and output layers so that the network does not converge to the undesirable local minima. Second, a proper choice of activation functions in the hidden nodes is crucial as it has been shown that some functions yield significant better result for certain problems [23]. Third, an appropriate initialization of the translation and dilation parameters is essential because this will lead to simpler network architecture and higher accuracy [24].

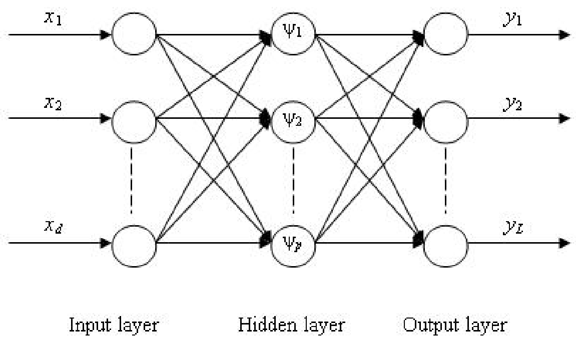

Fig. 3. WNNs with d input nodes, m hidden nodes, and L output nodes.

The selection of the translation vectors for WNNs is of paramount importance. An appropriate initialization of the translation vectors will do a good job of reflecting the essential attributes of the input space, in such a way that the WNNs begin its learning from good starting points and could lead to the optimal solution. Among the notable proposed approaches are the ones given by the pioneers of WNNs themselves, where the translation vectors are chosen from the points located on the interval of the domain of the function [26]. In [10], a dyadic selection scheme realized using the *K*-means clustering algorithm was employed. In [13], the translation vectors were obtained from the new input data. An explicit formula was derived to compute the translation vectors to be used for the proposed composite function WNNs [3]. In [24], an enhanced fuzzy *C*-means clustering algorithm, termed modified point symmetry-distance fuzzy *C*-means (MPSDFCM) algorithm, was proposed to initialize the translation vectors. By incorporating the idea of symmetry similarity measure into the computation, the MPSFCM algorithm was able to find a set of fewer yet effective translation vectors for the WNNs, which eventually led to superb generalization ability in microarray study. In short, the utilization of different novel clustering algorithms in WNNs aim at simpler algorithm complexity and higher classification accuracy from the WNNs.

In this study, the type-2 fuzzy *C*-means (T2FCM) clustering algorithm [16] was proposed to initialize the translation vectors of WNNs. Its clustering effectiveness as well as its robustness to noise has motivated the investigation on the feasibility of T2FCM in selecting the translation vectors of the WNNs. For comparison purposes, the use of *K*-means (KM) and the conventional type-1 fuzzy *C*-means (FCM-1) algorithms in initializing the WNNs translation vectors were also considered.

3.1 Type-2 Fuzzy *C*-Means Clustering Algorithm

Rhee and Hwang [16] proposed an extension to the conventional FCM-1 clustering algorithm by assigning membership grades to type-1 membership values. They pointed out that the conventional FCM-1 clustering may result in undesirable clustering when noise exists in the input data. This is because all the data, including the noise, will be assigned to all the available clusters with a membership value. As such, a triangular membership function is proposed, as shown in the following equation:

$$a_{ij} = u_{ij} - \left(\frac{1-u_{ij}}{2} \right), \tag{2}$$

where u_{ij} and a_{ij} represent the type-1 and type-2 membership values for input j and cluster center i, respectively. The proposed membership function aims to handle the possible noise that might present in the input data. From Eq. 2, the new membership value, a_{ij}, is defined as the difference between the old membership value, u_{ij} and the area of the membership function, where the length of the base of each of the triangular function is taken as 1 minus the corresponding membership value obtained from FCM-1.

By introducing a second layer of fuzziness, the T2FCM algorithm's concept still conforms to the conventional FCM-1 method in representing the membership values. To illustrate, it can noted from Eq. 2 that a larger value of FCM-1 value (closer to 1) will yield a larger value of T2FCM value as well.

Since the proposed T2FCM algorithm is built upon the conventional FCM-1 algorithm, the formula used to find the cluster centers, c_{ij} , can now be obtained from the following equation that has been modified accordingly, as shown below:

$$c_i = \frac{\sum_{j=1}^{N} a_{ij}^m x_j}{\sum_{j=1}^{N} a_{ij}^m}, \tag{3}$$

where *m* is the fuzzifier, which is commonly set to a value of 2.

The algorithm for T2FCM is similar to the conventional FCM-1, which aims to minimize the following objective function:

$$J_m(U,V) = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^m \| x_j - c_i \|^2, \tag{4}$$

but it differs in the extra introduced membership function and also the equation that has been modified to update the cluster centers. In general, the algorithm proceeds as follows:

1. Fix the number of cluster centers, *C*.
2. Initialize the location of the centers, c_i, $i = 1, 2, \dots, C$, randomly.
3. Compute the membership values using the following equation:

$$U = [u_{ij}] = \left[\left(\sum_{k=1}^{C} \left(\frac{\| x_j - c_i \|}{\| x_j - c_k \|} \right)^{\frac{2}{m-1}} \right)^{-1} \right]. \tag{5}$$

4. Calculate the new membership value, a_{ij} from the values of u_{ij} using Eq. 2.
5. Update the cluster centers using Eq. 3.
6. Repeat steps 3-5 until the locations of the centers stabilize.

The algorithm for T2FCM is summarized in the flowchart shown in Fig. 4.

3.2 *K*-fold Cross Validation

In statistical analysis, *k*-fold cross validation is used to estimate the generalization performance of classifiers. Excessive training will force the classifiers to memorize the input vectors, while insufficient training will result in poor generalization when a new input is presented to it. In order to avoid these problems, *k*-fold cross validation is performed.

To implement the *k*-fold cross validation, the samples are first randomly partitioned into k>1 distinct groups of equal (or approximately equal) size. The first group of samples is selected as the testing data initially, while the remaining groups serve as training data. A performance metric, for instance, the classification accuracy, is then measured. The process is repeated for *k* times, and thus, the *k*-fold cross validation has the advantage of having each of the sample being used for both training and testing. The average of the performance metric from the *k* iterations is then reported. In this study, *k* is chosen as 10.

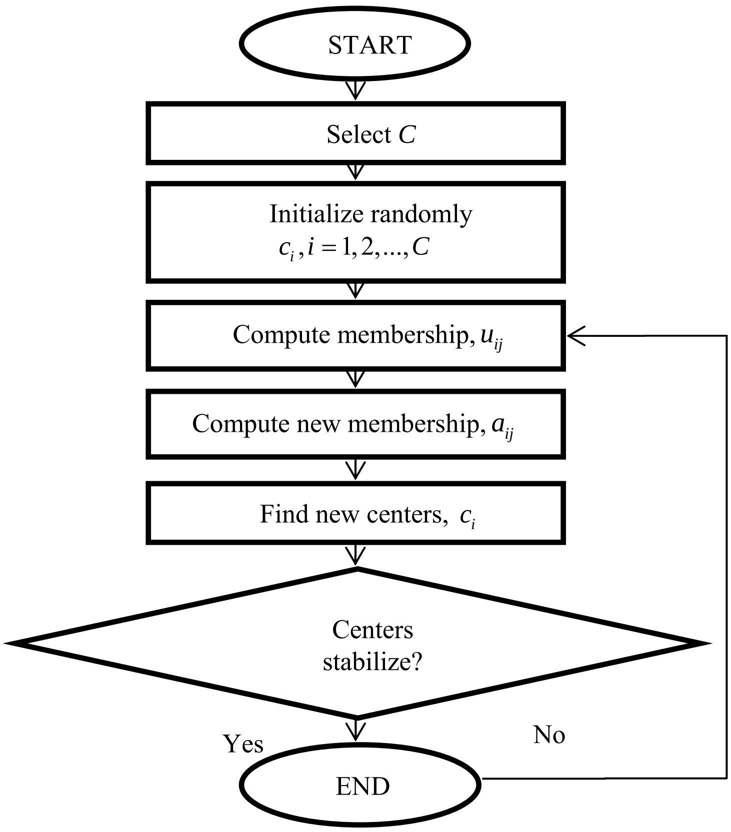

Fig. 4. Algorithm for T2FCM.

4 Results and Discussion

The binary classification task between normal subjects and epileptic patients was realized using the WNNs models. The activation function used in the hidden nodes is the Morlet wavelet function. During the training process, a normal EEG signal was indicated by a single value of 0, while an epileptic EEG signal was labeled with a value of 1. During the testing stage, a threshold value of 0.5 was used, that is, any output from WNNs which is equals to or greater than 0.5 will be reassigned a value of 1; otherwise, it will be reassigned a value of 0. The simulation was carried out using the mathematical software MATLAB® version 7.10 (R2010a). The performance of the proposed WNNs was evaluated using the statistical measures of classification accuracy, sensitivity and specificity. The corresponding classification results between the normal and epileptic EEG signals by using the WNNs-based classifier with different initialization approaches are listed in Table 1.

In terms of the classification accuracy, the translation vectors generated by the conventional KM clustering algorithm gave the poorest result, where an overall accuracy of 94.8% was obtained. The WNNs that used the conventional FCM-1 clustering algorithm reported an overall accuracy of 97.15%. The best performance was obtained by the classifier that employed the T2FCM algorithm, which yielded an overall classification accuracy of 98.87%.

As shown in Table 1, a steady increase in the classification accuracy was noticed when the KM clustering algorithm was substituted with FCM algorithm, and subsequently T2FCM algorithm. FCM outperformed the primitive KM algorithm because the soft clustering employed can assign one particular datum to more than one cluster. On the contrary, KM algorithm, which used hard or crisp clustering, assigns one datum to one center only, and this degrades greatly the classification accuracy. While FCM relies on one fuzzifier, T2FCM adds a second layer of fuzziness by assigning a membership function to the membership value obtained from the type-1 FCM membership values.

In the field of medical diagnosis, the unwanted noise and outliers produced from the signals or images need to be handled carefully, as they will affect and skew the results and analysis obtained afterwards. In this regard, the concept of fuzziness can be incorporated to deal with these uncertainties. Outliers or noise can be handled more efficiently and higher classification accuracy can be obtained via the introduction of the membership function. The noise in the biomedical signals used in this work has thus been handled via two different approaches. The first treatment is in the

Table 1. The performance metrics for the binary classification problem.

Initialization methods	Performance metric		
	Sensitivity	Specificity	Accuracy
KM	85.00	97.30	94.80
FCM	93.82	97.92	97.15
T2FCM	94.96	99.43	98.87

Table 2. Performance comparison of classification accuracy obtained by the proposed WNNs and other approaches reported in the literature

Feature Selection Method	Classifier	Accuracy	References
Time Frequency Analysis	ANNs	97.73	[20]
DWT with KM	MLPs	**99.60**	[15]
DWT	MLPs	97.77	[8]
Approximate Entropy	ANNs	98.27	[8]
This Work		**98.87**	

feature selection stage, where the 10^{th} and 90^{th} percentiles of the absolute values of the wavelet coefficients were used instead of the minima and maxima values. The second way is via the T2FCM clustering algorithm used when initializing the translation parameters for the hidden nodes of WNNs. The clustering achieved by T2FCM proves to result in more desirable locations compared to the conventional KM and FCM-1 methods, as reflected in the higher overall classification accuracy.

Numerous epileptic detection approaches have been implemented in the literature using the same benchmark dataset as in this study. For the sake of performance assessment, comparison of the results with other state-of-the-art methods reported in the literature was included, as presented in Table 2. As depicted in this table, the proposed WNNs with T2FCM initialization approach outperformed the others generally. However, the achieved classification accuracy of 98.87% by the proposed model was inferior to the multilayer perceptrons (MLPs)-based classifier as described in [15], which might be attributed to their feature extraction method. Instead of using basic statistical features, the authors used the KM clustering algorithm to find the similarities among the wavelet coefficient, where the obtained probability distribution from the KM was used as the input of the MLPs-based classifier. A better set of deterministic features might be obtained from this approach, which will be an interesting topic to pursue in future. However, it is pertinent to note that the MLPs-based classifiers are subject to slow learning deficiency and getting trapped in local minima easily.

In order to evaluate the statistical significance of the obtained results, statistical test on the difference of the population mean of the overall classification accuracy was performed using the *t* distribution. The experiment was run 10 times to obtain the values of the summary statistics, namely, the mean and the standard deviation of the samples. The 1% significance level, or α=0.01 was utilized to check whether there is significant difference between the two population means. Two comparisons were done, namely, between KM and T2FCM, and between FCM and T2FCM. The formula for the test statistics is given by:

$$t = \frac{\left(\overline{x}_1 - \overline{x}_2\right) - \left(\mu_1 - \mu_2\right)}{s_{\overline{x}_1 - \overline{x}_2}}, \tag{6}$$

where $\overline{x}_1$ and $\overline{x}_2$ are the sample means; μ_1 and μ_2 are the population means; and $s_{\overline{x}_1 - \overline{x}_2}$ is the estimate of the two standard deviations.

For both cases, the values of the test statistic obtained fall in the rejection region. So the null hypothesis is rejected and it is concluded that there is significant difference between the classification accuracy obtained using the different initialization methods, that is, the performance of T2FCM is superior to those of KM and FCM.

5 Conclusions

In this paper, a novel seizure detection scheme using the improved WNNs with T2FCM initialization approach was proposed. Based on the overall classification accuracy obtained from the real world problem of epileptic seizure detection, it was found that the proposed model outperformed the other conventional clustering algorithms, where an overall accuracy of 98.87%, sensitivity of 94.96% and specificity of 99.43% were achieved. The initialization accomplished via T2FCM has proven that the algorithm can handle the uncertainty and noise in the EEG signals better than the conventional KM and FCM-1 algorithms. This again suggested the prospective implementation of the proposed method in developing a real time automated epileptic diagnostic system with fast and accurate response that could assist the neurologists in their decision making process.

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References

1. Adeli, H., Zhou, Z., Dadmehr, N.: Analysis of EEG records in an epileptic patient using wavelet transform. J Neurosci Meth 123, 69-87 (2003)
2. Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., Elger, C. E.: Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. Phys Rev E 64, (2001)
3. Cao, J. W., Lin, Z. P., Huang, G. B.: Composite function wavelet neural networks with extreme learning machine. Neurocomputing 73, 1405-1416 (2010)
4. Ebrahimpour, R., Babakhani, K., Arani, S. A. A. A., Masoudnia, S.: Epileptic Seizure Detection Using a Neural Network Ensemble Method and Wavelet Transform. Neural Netw World 22, 291-310 (2012)
5. Gandhi, T. K., Chakraborty, P., Roy, G. G., Panigrahi, B. K.: Discrete harmony search based expert model for epileptic seizure detection in electroencephalography. Expert Syst Appl 39, 4055-4062 (2012)
6. Ghosh-Dastidar, S., Adeli, H., Dadmehr, N.: Mixed-band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection. IEEE transactions on bio-medical engineering 54, 1545-1551 (2007)
7. Ghosh-Dastidar, S., Adeli, H., Dadmehr, N.: Principal component analysis-enhanced cosine radial basis function neural network for robust epilepsy and seizure detection. IEEE transactions on bio-medical engineering 55, 512-518 (2008)

8. Guo, L., Rivero, D., Dorado, J., Rabunal, J. R., Pazos, A.: Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks. J Neurosci Meth 191, 101-109 (2010)
9. Guo, L., Rivero, D., Pazos, A.: Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks. J Neurosci Meth 193, 156-163 (2010)
10. Hwang, K., Mandayam, S., Udpa, S. S., Udpa, L., Lord, W., Atzal, M.: Characterization of gas pipeline inspection signals using wavelet basis function neural networks. NDT and E Int 33, 531-545 (2000)
11. Kandaswamy, A., Kumar, C. S., Ramanathan, R. P., Jayaraman, S., Malmurugan, N.: Neural classification of lung sounds using wavelet coefficients. Comput Biol Med 34, 523-537 (2004)
12. Kumar, S. P., Sriraam, N., Benakop, P. G., Jinaga, B. C.: Entropies based detection of epileptic seizures with artificial neural network classifiers. Expert Syst Appl 37, 3284-3291 (2010)
13. Lin, C.-J.: Nonlinear systems control using self-constructing wavelet networks. Appl Soft Comput 9, 71-79 (2009)
14. Naghsh-Nilchi, A. R., Aghashahi, M.: Epilepsy seizure detection using eigen-system spectral estimation and Multiple Layer Perceptron neural network. Biomed Signal Proces 5, 147-157 (2010)
15. Orhan, U., Hekim, M., Ozer, M.: EEG signals classification using the K-means clustering and a multilayer perceptron neural network model. Expert Syst Appl 38, 13475-13481 (2011)
16. Rhee, F. C. H., Hwang, C. A type-2 fuzzy C-means clustering algorithm. In: Proceedings of the 20th IEEE FUZZ Conference, pp 1926-1929. IEEE Press, New York (2001)
17. Subasi, A.: EEG signal classification using wavelet feature extraction and a mixture of expert model. Expert Syst Appl 32, 1084-1093 (2007)
18. Subasi, A., Gursoy, M. I.: EEG signal classification using PCA, ICA, LDA and support vector machines. Expert Syst Appl 37, 8659-8666 (2010)
19. Tang, Y., Durand, D. M.: A tunable support vector machine assembly classifier for epileptic seizure detection. Expert Syst Appl 39, 3925-3938 (2012)
20. Tzallas, A. T., Tsipouras, M. G., Fotiadis, D. I.: Automatic Seizure Detection Based on Time-Frequency Analysis and Artificial Neural Networks. 2007, (2007)
21. Ubeyli, E. D.: Wavelet/mixture of experts network structure for EEG signals classification. Expert Syst Appl 34, 1954-1962 (2008)
22. Ubeyli, E. D.: Combined neural network model employing wavelet coefficients for EEG signals classification. Digit Signal Process 19, 297-308 (2009)
23. Zainuddin, Z., Ong, P.: Modified wavelet neural network in function approximation and its application in prediction of time-series pollution data. Appl Soft Comput 11, 4866-4874 (2011)
24. Zainuddin, Z., Ong, P.: Reliable multiclass cancer classification of microarray gene expression profiles using an improved wavelet neural network. Expert Syst Appl 38, 13711-13722 (2011)
25. Zandi, A. S., Javidan, M., Dumont, G. A., Tafreshi, R.: Automated Real-Time Epileptic Seizure Detection in Scalp EEG Recordings Using an Algorithm Based on Wavelet Packet Transform. Ieee T Bio-Med Eng 57, 1639-1651 (2010)
26. Zhang, Q. G., Benveniste, A.: Wavelet Networks. Ieee T Neural Networ 3, 889-898 (1992)