Automatic Detection of Epileptic Seizures in EEG Using Machine Learning Methods

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Abstract: - Epilepsy is a common neurological disorder in which the sudden onset of seizures can cause delirium, body twitching, foaming at the mouth and other symptoms requiring immediate treatment. Electroencephalogram (EEG) is the primary method for objectively detecting epilepsy in patients and must be conducted by a trained physician or specialist. Therefore, the development of methods for the rapid and accurate diagnosis of epilepsy could potentially save considerable time and cost. The This study uses Discrete Wavelet Transform to analyze physiological EEG parameters and retrieve a plurality of sub-bands. Multiple classification methods are used to compare the diverse data to select the most suitable method for classifying epilepsy EEG data and to develop a diagnostic mode. The results found that C4.5 in the sub-D2 produced diagnoses with an accuracy of up to 90%. Rule-based of decision trees can be used to quickly analyze large amounts of data, thus accelerating epilepsy diagnosis.

Key-Words: - Electroencephalograph, Epilepsy, Discrete Wavelet, Machine Learning

1 Introduction

Epilepsy is a common neurological disorder that can produce sudden seizures. In most cases, the onset occurs before the age of 19, with about 80% taking place before the age of 10. Epilepsy is caused by abnormal cellular discharge in the brain, with symptoms including delirium, body twitching, trismus, foaming at the mouth, etc.

Electroencephalograph (EEG) signals are primarily used for the clinical detection and diagnosis of epilepsy. Epilepsy is recurrent and often has features abnormal brain discharges which can damage brain cells, making treatment challenging. Most epilepsy patients use medication to control their symptoms, but treatment is not always effective, sometimes requiring non-drug adjunctive therapy such as surgery.

This study uses discrete wavelet transform to analyze physiological EEG parameters and retrieve a plurality of sub-bands. Multiple classifications, including Decision tree (C4.5), support vector machine (SVM), neural networks (NN) and Bayes nets (BNs) are used to compare diverse data to select parameters more suitable for classifying epilepsy electroencephalogram (EEG) data, thus allowing for the development of a diagnostic mode to save considerable time and cost.

2 Related Works

2.1 Epilepsy

Epilepsy is an innate or acquired brain disorder characterized by the excessive discharge of brain cells and repeated seizures. Multiple clinical symptoms usually accompany convulsions and/or unconsciousness. Epilepsy is a complex disorder, but fewer than 1/3 of cases are due to genetic transmission. Patients rely primarily on anticonvulsant drugs to reduce the frequency and severity of seizures.

2.2 Electroencephalography

The brain operates through electrical activity. Currents in the cerebral cortex are composed of cells with the potential difference between the other cell populations generated. These brainwaves can be detected by electrodes placed along the scalp surface in a p rocess called electroencephalography (EEG).

Using high temporal resolution, EEG can directly record brain activity, offering potential for non-invasive clinical diagnosis and longitudinal tracking of neurological conditions. Cerebral signals detected by EEG largely falls in the range of 1~20 Hz (activity outside this range is likely to be artifactual under standard clinical recording techniques). In clinical practice, waveforms are divided into bandwidths known as delta (0.5~4Hz), theta (4~7Hz), alpha (8~15Hz), and beta (16~31Hz) (Tatum, 2014).

2.3 Epileptic Seizure Detection

Breaking brainwaves into multiple sub-bands provides additional information unavailable in raw EEG signals, thus improving epileptic seizure detection (Adeli et al., 2007). But the extraction of features from the frequency domain is inefficient and, with exceptions, accuracy is generally not high. Using PSD as the characteristics, Ubeyli and Guler (2007) achieved accuracy rates of 95.53% and 98.6%, respectively, for mixture of experts (ME) and modified mixture of experts (MME). DWT in the time domain is the most practical method of EEG signal classification (Güler and Ubeyli, 2007, Güler and Ubeyli, 2005, Ocak, 2009, Subasi, 2007). DWT characteristic extraction is based on maximum, minimum, mean, and standard deviation (Güler and Ubeyli, 2005, Güler and Ubeyli, 2007).

3 Methodology

Brainwaves are divided into various sub-bands based on the discrete wavelet transform. Brainwave characteristics are extracted from various sub-bands. Also, different classification methods are adopted to detect epilepsy and their performances are compared with each other.

3.1 Discrete wavelet transform

Discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. It captures both frequency and location information and smooths highly variable raw data. A signal's DWT is calculated by passing it through a series of filters. The number of columns generated by the low pass filter preserves the original number of data columns, while the high frequency filter produces a high degree of variability in the number of data columns (Daubechies, 1990).

Figure 1 shows the structure of discrete wavelet transform. $x[n]$ is the input signal and N shows the length. $g[n]$ is the low pass filter which passes through with the impulse response and then output $L[n]$. $h[n]$ represents high pass filter with output $H[n]$. $\downarrow Q$ is the downsampling filter. "a" is the "a" level of in the wavelet transform structure.

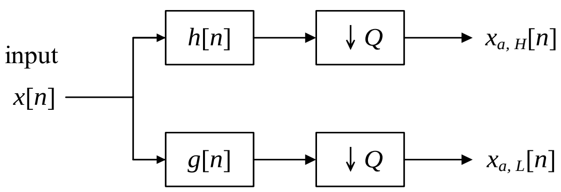

Fig. 1 Discrete Wavelet Transform structure

3.2 Decision tree

A decision tree is a decision support tool that uses a tree-like graph or model of decisions. An optimal decision tree is then defined as a tree that accounts for most of the data, while minimizing the number of levels. C4.5 is an algorithm developed by Ross Quinlan to generate a decision tree for use in classification. Therefore, C4.5 builds decision trees from a set of training data in the same way as ID3, using the concept of information entropy that is built top-down from a root node and involves partitioning the data into subsets that contain instances with homogenous values.

3.3 Support vector machine

Support Vector Machine (SVM) is a supervised learning model with associated learning algorithms that analyzes data used for classification and regression analysis. A SVM training algorithm builds a model that assigns new examples into different categories. A good SVM separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (Bastı et al., 2015).

3.4 Neural network

In an artificial neural network, simple artificial nodes, known as "neurons", "neurodes", "processing elements" or "units", are connected together to form a network which mimics a biological neural network. Neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, thus it is applied into various field.

3.5 Bayes net

Bayes Net (BN) represents a set of random variables and their conditional dependencies. It is used to creating various features of incidence and then calculates conditions of probability for any set of variables in the network. Bayes networks area also used for collocation and prediction.

3.6 Fuzzy c-means

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters and is frequently used in pattern recognition (Dunn, 1973; Bezdek, 1981). It is based on minimization of the objective function. Fuzzy partitioning is carried out through an iterative optimization of the objective function.

4 Experiment and Result

4.1 Samples

The dataset includes five different categories of patients (Andrzejak et al., 2001). EEG signals have often been used to detect epilepsy (Güler and Ubeyli, 2007; Tzallas et al., 2009; Ubeyli and Guler, 2007; Ubeyli, 2008). Categories 1 and 2 respectively represent brainwaves for healthy subjects with their eyes open and closed. Category 3 shows brainwaves from the hippocampal formation in epileptic patients. Category 4 is epilepsy seizure EEG focused on the hippocampus. Category 5 focuses on the brain's hippocampus of clinically confirmed epilepsy patients. Each category contains 100 samples, for a total of 500. Every 23.6 seconds is divided into a sampling frequency in the range of 0.53-40 Hz, with a sampling rate of 173.61Hz, and a resolution of 12 bits. Categories 1 and 2 are grouped into Set A (non-epileptic subjects) while categories 3~5 are Set B (epileptic subjects).

4.2 Data processing

The 500 samples were filtered through the discrete wavelet transform function in MATLAB R2012a, where db2 is a wave smoothing effect (Güler et al., 2005). Following the first discrete wavelet transformation, a high-pass filter and a low-pass filter are respectively used to produce sub-bands D1and A1. Sub-band A1 then proceeds to a second discrete wavelet transformation to generate sub-bands D2 and A2. A2 is used for third discrete wavelet transformation, and so on, for a total of 4 wavelet conversions. Figure 2 shows all sub-bands D1~D4 and A4.

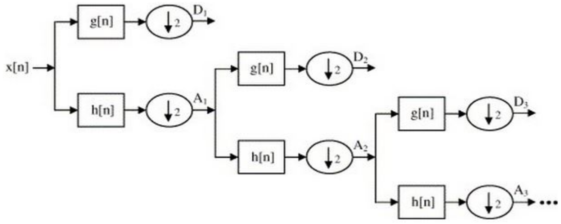

Fig. 2 Discrete wavelet transform process

4.3 Features extraction

Following the discrete wavelet transform of each sub-band, the value of maximum, minimum, mean, and standard deviation (SD) are used as EEG characteristics for epilepsy classification. Set A includes non-epileptic subjects and Set B is for epileptic subjects (Table 1).

4.4 Evaluation of Epilepsy seizure detection

This section compares the classification methods for epilepsy diagnosis. The effectiveness of the various methods was evaluated based on true positive rate (sensitivity) (TP-rate=TP/(TP+FN)), true negative rate (specificity) (TN-rate=N/(FP+TN)), false positive rate (FP-rate=FP/(FP+TN)) and false negative rate (FN-rate=FN/(TP+FN)). The precision rate is defined as TP/(TP+FP) and the recall rate is TP/(TP+FN). Accuracy is defined as (TP +TN) / (TP +FP + FN + TN). The *F*-measure combines precision and recall rate on the prediction of the positive class (*F*-measure = 2 × precision × recall / precision + recall). AUC is the area under the receiver operating characteristic curve calculated using MedCalc. The detection model is developed using different datamining methods including a multilayer perceptron neural network (NN), decision tree (C4.5), support vector machine (SVM), Naïve Bayes, (NB), Bayes net (BN) and Fuzzy c-means (FCM). The polynomial kernel is a kernel function commonly used with SVM. The dataset is divided 80/20 for training and testing. Tabel 2~6 presents the results of the D1~D4 and A4 sub-bands.

C4.5 has the highest performance in all measure indexes in most of sub-bands. The accuracy rate of Bayes Net in sub-bands D1~D4 is surpassed only by decision tree and has the higher accuracy rate in A4. The SVM in the D1~D4 subsample has higher false positive rate and is easily categorized as non-epileptic with status epilepticus (i.e., unclassifiable epilepsy). It has only better performance in sub-band A4. Accuracy rate of neural network is slightly higher in sub-bands D1 and A4. The performance of Naïve Bayes and FCM are weaker than other methods. The accuracy rate is the highest in the A4 sub-bands for most of methods. All methods in the D4 sub-bands result in low accuracy rates (i.e., below 70%).

Table 1 Features description of various Sub-bands

Dataset	*Extracted features*	*Sub-bands*				
		D_1	D_2	D_3	D_4	A_4
Set A	Maximum	125.54	233.66	652.19	903.58	787.93
	Minimum	-125.85	-289.51	-550.85	-852.35	-786.9
	Mean	-0.003	-0.004	0.031	-0.808	-37.572
	SD	2.994	10.379	36.96	48.755	29.684
Set B	Maximum	779.05	1548.7	3339.7	3789.2	6094.8
	Minimum	-863.56	-1847.7	-3710	-4376.5	-5339.8
	Mean	-0.005	-0.02	-0.06	-0.03617	-26.470
	Standard deviation	21.54	89.05	229.356	342.812	350.364

Table 2 Performance measure of different approaches in Sub-band D1

Methods	FPR	Precise	Recall	AUC	F-measure	G mean	Accuracy
C4.5	0.153	0.854	0.85	0.914	0.851	0.873	85.00%
MLP-NN	0.216	0.779	0.73	0.852	0.733	0.805	73.00%
SVM	0.62	0.384	0.62	0.500	0.475	0.634	62.00%
NB	0.292	0.716	0.59	0.796	0.578	0.713	59.00
BN	0.161	0.835	0.82	0.887	0.822	0.862	82.00%
Fuzzy-C means	0.593	0.507	0.915	0.661	0.652	0.610	61.00%

Table 3 Performance measure of different approaches in Sub-band D2

Methods	FPR	Precise	Recall	AUC	F-measure	G mean	Accuracy
DT	0.071	0.914	0.9	0.94	0.901	0.93	90.00
MLP-NN	0.376	0.628	0.57	0.567	0.573	0.645	57.00%
SVM	0.62	0.384	0.62	0.5	0.475	0.634	62.00%
NB	0.241	0.774	0.64	0.835	0.631	0.772	64.00
BN	0.106	0.881	0.86	0.938	0.862	0.909	86.00%
Fuzzy-C means	0.633	0.504	0.965	0.666	0.662	0.595	60.60%

Table 4 Performance measure of different approaches in Sub-band D3

Methods	FPR	Precise	Recall	AUC	F-measure	G mean	Accuracy
DT	0.182	0.826	0.82	0.864	0.822	0.849	82.00
MLP-NN	0.62	0.384	0.62	0.551	0.475	0.634	62.00%
SVM	0.62	0.384	0.62	0.5	0.475	0.634	62.00%
NB	0.255	0.779	0.6	0.785	0.578	0.758	60.00
BN	0.149	0.841	0.79	0.875	0.793	0.868	79.00%
Fuzzy-C means	0.450	0.513	0.710	0.63	0.596	0.625	61.40%

Table 5 Performance measure of different approaches in Sub-band D4

Methods	FPR	Precise	Recall	AUC	F-measure	G mean	Accuracy
DT	0.426	0.744	0.72	0.743	0.684	0.711	72.00
NN	0.647	0.418	0.56	0.61	0.459	0.578	56.00%
SVM	0.62	0.384	0.62	0.5	0.475	0.634	62.00%
NB	0.28	0.727	0.61	0.722	0.601	0.728	61.00
BN	0.215	0.818	0.65	0.718	0.636	0.806	65.00%
Fuzzy-C means	0.440	0.502	0.665	0.613	0.572	0.610	60.20%

Table 6 Performance measure of different approaches in Sub-band A4

Methods	FPR	Precise	Recall	AUC	F-measure	G mean	Accuracy
DT	0.145	0.848	0.83	0.886	0.832	0.867	83.00
NN	0.172	0.82	0.77	0.817	0.773	0.847	77.00
SVM	0.198	0.804	0.71	0.756	0.709	0.819	71.00
NB	0.198	0.804	0.71	0.855	0.709	0.819	71.00
BN	0.11	0.882	0.87	0.904	0.872	0.906	87.00
Fuzzy-C means	0.253	0.687	0.835	0.791	0.754	0.790	78.20%

As previously mentioned, C4.5 produces the best accuracy, especially in Sub-band D2, and handles large data sets more quickly than other epilepsy EEG data classification methods. MLP-NN and SVM perform poorly for epilepsy detection in sub-bands D1~D4. Sub-band A4 has the highest classification accuracy results and is suitable for epilepsy detection from EEG data.

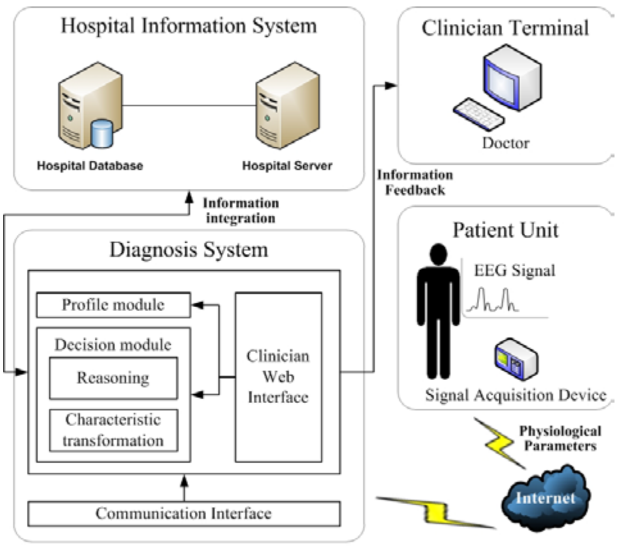

Fig. 3 A framework of automatic epileptic seizure detection

5 Conclusion

In comparison with all data mining methods, the C4.5 is better than other data mining methods in the detection of epileptic seizure. Applying C4.5 to the D2 sub-band offers the highest accuracy (90%) for epilepsy seizure detection based on EEG, providing physicians with a fast and effective tool for epilepsy diagnosis. The result of our proposed method is very meaningful and can be easily incorporated with a client-server framework to assist automatic detection of epileptic seizures. For example, as shown in Fig. 12, a n automatic epileptic seizure detection prototyping system is implemented based on the rule-based reasoning module of decision tree C4.5.

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