

A DISCRIMINATIVE APPROACH TO AUTOMATIC SEIZURE DETECTION IN MULTICHANNEL EEG SIGNALS

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ABSTRACT

The aim of this paper is to introduce the application of Random Forests to the automated analysis of epileptic EEG data. Feature extraction is performed using a discrete wavelet transform to give time-frequency representations, from which statistical features based on the wavelet decompositions are formed and used for training and classification. We show that Random Forests can be used for the classification of ictal, inter-ictal and healthy EEG with a high level of accuracy, with 99% sensitivity and 93.5% specificity for classifying ictal and inter-ictal EEG, 90.6% sensitivity and 95.7% specificity for the windowed data and 93.9% sensitivity for seizure onset classification.

1. INTRODUCTION

Epilepsy affects between 0.6–0.8% of the world's population and for 25% of these people there is not enough treatment available for them to reach a level of control over their condition. Epilepsy can be defined as suffering two or more unprovoked epileptic seizures occurring within a time frame of two years, with 'unprovoked' referring to the absence of other conditions that may cause seizures, such as alcohol withdrawal [1]. Seizures can be defined by the physical changes in a sufferer, caused by hyper-synchronous neural activity, such as involuntary muscle movements and the alteration of conscious state. It is also associated with abnormal Electroencephalography (EEG) readings. The diagnosis of epilepsy however, is made particularly complex by the inconsistent nature of the occurrence of seizures and the nature of seizures varying significantly between patients, including a high variance in EEG characteristics. The identification of seizure location in EEG data is an arduous and subjective process, requiring a large amount of time and expert knowledge in order to give an estimate of seizure location. It is thus desirable to develop automated techniques to recognize these seizures in order to assist or potentially replace the need for searching by a human expert. It has even been speculated that the efficient algorithmic identification of epileptic seizures may lead to a device that could be implanted under the skull for the automatic delivery of medicine to the brain designed to stop a seizure, when an episode onset is detected, e.g. [2].

The way in which algorithmic epileptic classifiers are

tested in the literature varies. For example, the work of [3] evaluates classifiers for the detection of seizure onset, which means that the metric used to evaluate the performance is based on the positive detection of a seizure during any point during a given seizure's timespan. [4] uses the same dataset to assess a classifier for the correct classification of all windows calculated for a given dataset. This means that the number of correctly classified windows becomes the appropriate metric.

This paper is concerned with both the patient-specific and patient non-specific automated classification of EEG signals using discriminative features and randomized decision trees. The work is inspired by research such as [3], which makes use of spectral feature vectors to train a Support Vector Machine (SVM) to detect seizure onset in pediatric EEG and also the research in [5] which takes a wavelet transform approach to extract time-frequency based features from EEG bands to classify non-epileptic, interictal (periods of time between seizures) and ictal (periods of seizure) segments of EEG data using an Artificial Neural Network (ANN). In this paper we detail the creation of similar time-frequency based features as the latter example, applied to both the detection of seizure onset in pediatric EEG and the classification of non-epileptic, inter-ictal and ictal EEG using Random Forests as a classifier. We also investigate the classifier's overall discriminative ability when identifying windows of data across the whole of a seizure, in addition to its onset. It is intended that these three tasks covering two separate datasets will provide a wide-reaching set of results. It is also the intention of this research that enough information is provided to the reader in order to re-create the software, as attempts to do this with some previous research in the literature has proven difficult.

2. METHOD

The proposed method consists of EEG signal pre-processing, feature extraction, classifier training and classification. This study investigates the classification of two datasets. The first is segmented into ictal, inter-ictal and normal EEG (known here as dataset 1) and the second is taken from 24 epilepsy patients (known here as dataset 2). Dataset 1 contains artifact free data taken during a short recording session and was chosen for the purposes of evaluating the discriminative ability of random forests when presented with such ideal data. Dataset

2 contains a more varied collection of samples in regards to recoding environments and so provides a more challenging task for the classifier. These datasets are explained in detail in a later section.

2.1. Pre-Processing

Pre-processing involves filtering the raw EEG signal to remove artifacts; statistical features of the time-frequency decomposition of the filtered signal are then taken in order to provide a representation of the variance in the underlying EEG data. This allows us to present the labeled feature vectors to a machine learning algorithm to allow for accurate generalization and classification. Once a dataset is loaded, the pre-processing is performed to remove artifacts caused by, for example, eye-blinks and muscle movements, which is performed by filtering algorithms; usually a band-pass filter set to approximately 0.5Hz and 80Hz (although these values vary between studies). In our research, for both datasets, an FIR low-pass filter was used set at 80Hz.

2.2. Feature Extraction

Seizures in EEG data are defined by characteristic activity, which is often very different between patients and is sensitive to the spatial location of events. Seizures are not the only brain related phenomena that can cause seizure-like EEG activity and so it is inherent to the task of seizure identification to differentiate seizures from activities such as sleep states. In order to successfully identify seizures, features extracted from EEG signals need to carry sufficient discriminative power to allow for the differentiation between normal and abnormal EEG. In addition, they also need to be physiologically appropriate to the task of seizure detection, such that they are capable of representing the fundamental functioning or mis-functioning of the physical neurons during periods of ictal or inter-ictal states.

Time domain features, often heuristic driven, have been used in identifying seizures. For instance, in [6] the authors used spike rhythmicity (referring to the number of spikes in the data crossing a 50% of the highest amplitude spike threshold) and the relative spike amplitude (the maximum value of the spikes that pass a threshold value), following the filtering and subtraction of the resultant signal from the original signal, to characterize seizure signals. The paper also uses these features in combination with frequency-domain values to create an ANN based classifier. This combination of feature sources may be a future direction for our research since they achieve a high accuracy; however only one dataset is used in the evaluation and so it is not clear how discriminative the classifier will be when presented with seizure-like activity.

Frequency domain features, typically obtained from the frequency information derived from the Fourier transform of the time domain signal, are commonly used in EEG feature extraction, since much of the useful EEG information

resides between the bands of delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz) and beta (13-30Hz) and the Fourier transform allows spectral content to be easily extracted according to these ranges. In [3], the authors used the power of the signal in frequency domain ranges and their historical values as features for a SVM to classify seizure onset. A short time Fourier transform was used to obtain the total power of eight equal sub-bands of the power-frequency domain between 0.5-25Hz at two second intervals. In order to take into account the evolution of the signal at any given point, the previous three magnitude values in relation to a given data point were concatenated and added to the feature vector. Due to the localized nature of some seizure activity, it is important to take into account where any given EEG activity is taking place. To this end, each channel of EEG data was processed separately and added to the feature vector. Maintaining a spatial representation of the EEG activity in the feature vector is an important aspect of our research due to the localization of some EEG activity and this was inspired by the research in [3]. This approach appears useful such that a given window is evaluated according to previous values, which should lower the number of false detections. However in doing so, the feature vectors become very large which increases the processing time needed to train a SVM. The idea of including the previous epochs as a history in each feature vector was experimented with during this research, however it was found in this case to have a detrimental effect on the accuracy of the system. In addition, [3] does not investigate the potential of using the SVM to classify healthy EEG data.

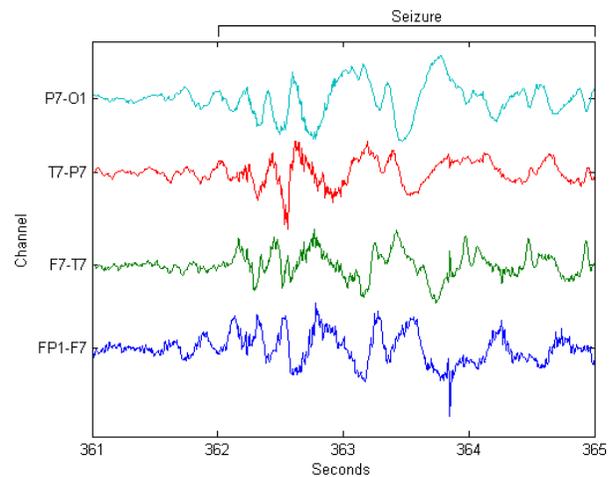


Fig. 1. High amplitude slow-wave activity indicative of an epileptic seizure.

Wavelet transforms have the advantage of being appropriate for the analysis of non-stationary signals such as epileptic EEG and so transient events could be located in time from a multi-resolution view of the signal. The Discrete Wavelet Transform (DWT) allows the decomposition of a signal

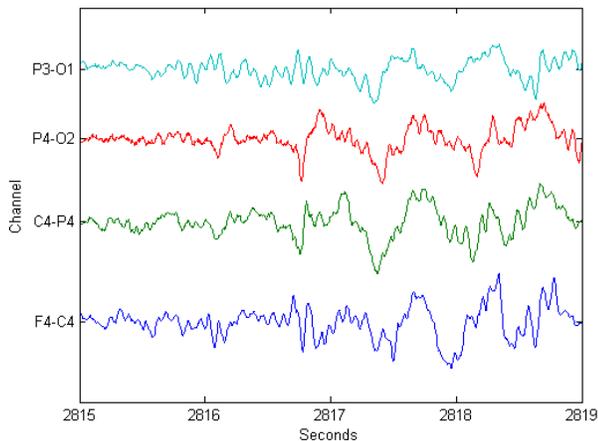


Fig. 2. Similar slow-wave activity to a seizure, however no seizure is present.

(mother wavelet) into an infinite series of wavelets, which can all be used to reconstruct the original signal. The DWT produces time-frequency representation, with good frequency localisation at low frequency ranges and good time localisation at higher frequency ranges. This makes it particularly suitable for EEG analysis due to the location of useful information in the lower frequency bands. It is for these reasons that we chose the DWT to implement the feature extraction, which is performed with using a Debauches of order 4 (db4) discrete wavelet transform in order to decompose each channel of data into 6 sub bands. The db4 was chosen due to its smoothing effect which can make it more appropriate for detecting EEG events, as shown in [7]. Only the bands corresponding to 0.5 to approximately 20Hz [8] were used for feature construction as these are the bands that contain the most prominent features during seizures.

2.3. Feature Selection

An example method of feature selection is [4] which uses the maximum, minimum, mean and standard deviation features from a Wavelet Transform of the signal. The paper documents the use of both a Multi-layer Perceptron network in combination with an Radial Basis Function neural network.

For dataset 1 the median, standard deviation and the 90th and 10th percentile (percentile features as in [9] and standard deviation feature as in [5]) for each wavelet between 0-25Hz are taken to construct a feature vector of size 4. The features for dataset 2 were calculated as simply the median of each epoch window and taken from each electrode. These features were selected through experimentation with various feature combinations and these were selected as they gave a high level of accuracy. The median feature and the 90th and 10th percentile features were used with the motivation

of minimizing the effect of spikes in the data which would have a tendency to dominate a feature such as the sum of the power. These features were decided upon in order to gain an insight into the changes in distribution of power in the signal. All features were calculated using the absolute values of each sample.

For each feature vector from dataset 2 covering (for example) 28 electrodes, 112 elements are included in a feature vector, constructed from 4 sub-bands of EEG. Separating activity from each electrode by using separate vector elements for each encodes the position of brain activity into the construction of the feature vector. This allows for the RF to classify a seizure based on the spatial location of the EEG activity resembling a seizure. This is useful when differentiating between seizure and seizure-like states.

For seizure onset detection, the selection of seizure data was intentionally biased towards the onset of the seizure by using the first 33.3% of the seizure data to construct the feature vectors. A similar technique was used in [3] which uses the first 20 seconds of seizure data for each patient, however it was thought that since the seizures vary greatly in length (sometimes as small as 6 seconds or long as 3 minutes) that a percentage of each seizure would be more appropriate. For our purposes it was found that using a percentage did provide us with a higher detection rate compared to a static number of seconds per seizure. When evaluating the classifier for total window classification however, all of the seizure data available for each patient was used.

2.4. Classification

This paper is concerned with the use of Random Forests (RF) which is an ensemble learning technique based on decision trees. The technique of RF is to create many of decision trees using random selections of features each time. The whole set of trees then vote on a final decision. RF has previously been shown to be applicable to the task of classifying mental tasks in EEG [10]. Additionally, other theoretical arguments could be made for their use. For example, Skurichina et al. [11] argue that a both high dimensional dataset, such as is usually the case with EEG, and a low quantity of sample data can lead to a weak classifier. This can cause a classifier to be unstable and so may give very different results based on the given training data. As mentioned in [10], the application of ensemble learning could potentially overcome this issue through the amalgamation of results from multiple weak classifiers, in the case of RF, from random subsets of the training data which compliments the high dimensionality of the EEG data. RF is also capable of adapting to new data without having to re-train the whole model. This, in addition to its high speed classification ability, holds promise for real time EEG monitoring and classification.

To the best of our knowledge there is currently no evaluation of RF when applied to the task of epileptic seizure recog-

nition in EEG. This in addition to the suggestion elsewhere that ensemble based classifiers can be useful in the domain of EEG, we propose to investigate their application to this end. For the construction of the RF classifier, two parameters were used: a value indicating the number of decision trees and a ratio value. An over-populated RF will negatively impact training times and under-population will give inaccurate predictions. The ratio value controls the size of the subset of features used for training in order to control overfitting of the model. The RF was constructed using 120 trees and a ratio value of 0.6 for dataset 1. For dataset 2, 40 trees were used and a ratio value of 0.84. These parameters were selected empirically by iteration through the sets of potential values.

2.5. Evaluation Method

The nature of a seizure in terms of EEG varies significantly between patients, however it remains generally consistent for an individual patient. Because of this, a patient-specific approach to seizure detection was taken during the analysis of dataset 2, and so for a given patient only EEG from that patient was used during training and classification. Dataset 1 was used to create a patient non-specific classifier.

2.5.1. Datasets

Dataset 1 includes epileptic and healthy data. The epileptic data includes both ictal and inter-ictal subsets and is described in detail in [1]. In the first instance, 50% of each subset was used to construct the training feature vectors and the remaining 50% of each file was used for classification. Classification was performed on both ictal and inter-ictal EEG in order to test both the seizure identification and epilepsy diagnosis capabilities of the classifier. Once 50% of the data has been classified and the positive and negative classification assessed, the 50% used for classification was then used for training and the previous training set became the classification set. For both ictal and inter-ictal this cycle was repeated and an average specificity and sensitivity taken. The cycle was repeated until a consistent average value was observed.

Dataset 2 consists of 198 seizures and was obtained from work at a children's hospital from 24 patients. This dataset originated from work in [12]. For each patient, the data was split into 2 second non-overlapping epochs. We experimented with the use of overlapping epochs, however this was found to have a detrimental effect on accuracy. The classifier was trained with 35 times as many negative epochs as there were positive epochs. It was important to get this balance right since too many negative samples would lead to a low detection rate and too little then the classifier would not be able to discriminate between a seizure and, for example, certain sleep stages or artifacts due to a lack of exposure to these events. Each patient's EEG was assessed with each seizure from a given patient left out during a training session and that seizure used for the classification stage. This was performed

iteratively for all seizures. The whole set of negative samples from a file containing a seizure that was to be classified was not used in training in order to prevent accuracy being artificially increased due to the high temporal correlation present in EEG. Ictal classifications of 6 seconds duration or more was considered as being a positive classification.

3. RESULTS

Sensitivity for seizure onset was calculated as the number of seizures identified as a percentage of the total number available. In all other cases, Sensitivity and Specificity was calculated based on overall classification (for dataset 1) or window classification (dataset 2).

The results for dataset 1 are 99% sensitivity and 93.5% specificity which makes 96.25% accuracy. An example comparison would be with [9] which uses dataset 1 and investigates a wavelet neural network which scored 94.96% sensitivity, which compares favorably with our results. However they also reach a specificity of 99.43%. Orosco et al. [13] provide a comprehensive review of research into epileptic classification that has used dataset 1 and provide a useful reference for comparison. The overall accuracy of all reviewed work in [13] is 94.53% which is just below the accuracy achieved in our research.

The overall results for dataset 2 in regards to window classification are 93.05% sensitivity and 92.90% specificity. Per patient, the median specificity is 94.5% and mean is 93%. The highest specificity is for patient 10 at 98.5% although the lowest is patient 16 at 65.6% sensitivity. The false detection rate may be increased due to the positive classification of windows around the stated start and end times of a seizure in the data. For seizure onset identification we detected 94.9% of the seizures with a median false detection rate of 66 false detections per 24 hours. Per patient, the maximum specificity is for patient 18 which has 285 false detections per 24 hours. The lowest is patient 6 which has 3 per 24 hours. The onset sensitivity is made lower due to patient 16 where only 5 of the 10 available seizures were detected and also patient 13 where only 9 of 12 were detected. So for the majority of the available patients, all of the seizures were detected during onset. For the same task, [3] uses an SVM to detect seizure onset and has a higher detection rate of 96% and a lower false detection rate of 2 false positives per 24 hours. Due to much less research being performed on dataset 2, comparing results is difficult. However our results can be compared to [4] which performs a similar task of creating a classifier to judge overall numbers of window classifications (not seizure onset identification). The results specified by their research have a lower sensitivity at 91.26% and the false detection rate is also higher at 13.51%.

Our results suggest that Random Forests are an effective tool for the classification of epileptic EEG. While the classification results do not appear to be highest in terms of all

Table 1. Final Results for Dataset 1

Sensitivity	Specificity	Accuracy
99%	93.5%	96.25%

Table 2. Final results for Dataset 2

Metric	Value
Window Classification Sensitivity	93.05%
Window Classification Specificity	92.90%
Window Classification Accuracy	92.97%
Seizure Onset Detection	94.9%
Seizure Onset False Detections	66 / 24 hours

metrics it is hoped that further investigation into the on-line capabilities of random forests may lead to useful research regarding real-time classification.

4. CONCLUSION

In this paper we have presented an effective method of detecting the location of epileptic seizures in large data files with high sensitivity and specificity levels. We have also shown that RF can be used to identify ictal and inter-ictal segments of EEG. In the future, this technique is hoped to be combined with sonification methods in order to fuse efficient human interaction with algorithmic seizure detection. Genetic algorithms have previously been used as a way of evolving the optimum selection of features [14] which may also be promising for searching the set of potential EEG features that may define a seizure. The research could also be extended to include values from sensors detecting other physiological markers of seizures such as muscle movement or eye blinking by extending the feature vector to include these values.

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