An Advanced Machine Learning Approach to Generalised Epileptic Seizure Detection

Paul Fergus, David Hignett, Abir Jaffar Hussain, and Dhiya Al-Jumeily

Liverpool John Moores University, Applied Computing Research Group,
Byrom Street, Liverpool, L3 3AF, UK
{P.Fergus,D.Hignett,A.Hussain,D.Aljumeily}@ljmu.ac.uk

Abstract. Epilepsy is a chronic neurological condition that affects approximately 70 million people worldwide. Characterised by sudden bursts of excess electricity in the brain manifesting as seizures, epilepsy is still not well understood when compared with other neurological disorders. Seizures often happen unexpectedly and attempting to predict them has been a research topic for the last 20 years. Electroencephalograms have been integral to these studies, as they can capture the brain's electrical signals. The challenge is to generalise the detection of seizures in different regions of the brain and across multiple subjects. This paper explores this idea further and presents a supervised machine learning approach that classifies *seizure* and *non-seizure* records using an open dataset containing 543 electroencephalogram segments. Our approach posits a new method for generalising seizure detection across different subjects without prior knowledge about the focal point of seizures. Our results show an improvement on existing studies with 88% for *sensitivity*, 88% for *specificity* and 93% for the area under the curve, with a 12% global error, using the *k-NN* classifier.

Keywords: Seizure, non-seizure, machine learning, classification, Electroencephalogram, oversampling.

1 Introduction

Epilepsy is a chronic condition of the brain, and causes repeated seizures, commonly referred to as fits. Epilepsy is said to affect one in every 103 people in the UK (500,000 approximately), according to epilepsy research UK[1], and 70 million people worldwide (Fazel, Wolf, Langstrom, Newton, & Lichtenstein, 2013). The risk of developing epilepsy is greatest at the extremes of life with incidences more common in the elderly than the young (Engel, 2013).

Seizures can be focal (partial) and exist in one part of the brain only, or they can be general and affect both halves of the brain. In a focal seizure, the excess electrical activity is confined to the occipital lobes, parietal lobes, frontal lobes, or temporal lobes. During a focal seizure, the person may be conscious and unaware that a seizure

[1] http://www.epilepsyresearch.org.uk

D.-S. Huang et al. (Eds.): ICIC 2014, LNBI 8590, pp. 112–118, 2014.

is taking place, or they may have uncontrollable movements or unusual feelings and sensations. During a general seizure, consciousness is normally lost and muscles may stiffen and jerk[2]. A diagnosis of epilepsy is made if a patient has had two or more unprovoked seizures[3], and diagnosis is made with the help of an electroencephalogram (*EEG*), which measures the electrical activity in the brain.

The majority of previous works on seizure detection have focused on patient-specific predictors, were a classifier is trained on one person and tested on the same person (Carney, Myers, & Deyer, 2011; Maiwald et al., 2004; Mormann, Andrzejak, Elgar, & Lehnertz, 2007; Shoeb, 2009). However, in this paper, the emphasis is on using *EEG* classification to generalise detection across all regions of the brain using multiple subject records, without prior knowledge of which region of the brain the seizure occurred. Several classifiers are evaluated using 171 *seizure* and 171 *non-seizure* blocks extracted from the 543 *EEG* segments of 24 patients suffering with epilepsy.

The structure, of the remainder, of this paper is as follows. Section 2 describes the underlying principles of Electroencephalography and the type of features extracted from Electroencephalography signals. Section 3 discusses the approach taken in this paper, while Section 4 describes the evaluation. The results are discussed in Section 5 before the paper is concluded in Section 6.

2 Electroencephalography and Feature Extraction

Electroencephalography (EEG) is the term given for the recording of electrical activity resulting from ionic current flows generated by neurons in the brain (Libenson, 2009) and is mainly used to evaluate seizures and epilepsy. In order to retrieve *EEG* signals, electrodes are placed on the scalp where odd numbered electrodes are placed on the left side of the scalp and even numbered electrodes on the right. The letters that precede the numbers represent brain regions (*Fp*) frontopolar, (*F*) frontal, (*T*) temperal, (*P*) parietal, (*C*) central, and (*O*) occipital (Libenson, 2009).

The collection of raw *EEG* signals is always temporal. However, for analysis and feature extraction purposes, translation, into other domains, is possible and often required. In order to obtain frequency parameters, several of the studies reviewed, have used Power Spectral Density (*PSD*). *Peak Frequency* is one of the features also considered in many studies. It describes the frequency of the highest peak in the *PSD*. During a seizure, *EEG* signals tend to contain a major cyclic component, which shows itself as a dominant peak in the *frequency domain* (Sanei & Chambers, 2007).

Meanwhile, Ning *et al.* (Ning & Lyu, 2012) found that *Median Frequency* displayed significant differences between *seizure* and *non-seizure* patients. By segmenting the *EEG* signal into five separate frequency bands for *delta* (δ: $0.5 \leq f \leq 4$ Hz), *theta* (θ: $4 \leq f \leq 8$ Hz), *alpha* (α: $8 \leq f \leq 12$ Hz): *beta* (β: $12 \leq f \leq 25$ Hz), and *gamma*

[2] http://www.epilepsy.org.uk
[3] http://www.who.int

(γ: 25 ≤ f), it was possible to predict 79 of 83 *seizures*, with a *sensitivity* value of 95.2%.

Root Mean Square (*RMS*) has also been considered a useful feature for distinguishing between *seizure* and *non-seizure* events. *RMS* measures the magnitude of the varying quantity and is a good signal strength estimator in *EEG* frequency bands (Abdul-latif, Cosic, Kimar, & Polus, 2004; Patel, Chern-Pin, Fau, & Bleakley, 2009).

Entropy has been used as a measure of the complexity, or uncertainty, of an *EEG* signal, were the more chaotic the signal is, the higher the *entropy* (Greene et al., 2008; Sanei & Chambers, 2007). Many authors agree that during a *seizure*, the brain activity is more predictable than during a normal, *non-seizure*, phase and this is reflected by a sudden drop in the *entropy* value (Aarabi, Fazel-Rezai., & Aghakhani, 2009; Diambra, de Figueiredo, & Malta, 1999; Greene et al., 2008; Iasemidis, 2003; Kelly et al., 2010). All of the above features are extracted from the raw dataset in this paper.

3 Generalisation of Epileptic Seizure Detection

The study in this paper focuses on discriminating between *seizure* and *non-seizure* *EEGs* across a group of 24 subjects. The classifiers are trained on all patient records and therefore, classification is generalised across all subjects using features from channels that capture the *EEG* in all parts of the brain.

3.1 Methodology

The *CHB-MIT* dataset used in this paper is a publicly available database from physionet.org that contains 686 scalp *EEG* recordings from 24 patients treated at the Children's Hospital in Boston. The subjects had anti-seizure medication withdrawn, and *EEG* recordings were taken for up to several days after.

3.1.1 Data Pre-processing

In the *CHB-MIT* database, each record was sampled at 256Hz, with 16-bit resolution. Signals were recorded simultaneously through twenty-three different channels, via 19 electrodes and a ground attached to the surface of the scalp.

A bandpass filter was applied to each of the 543 *EEG* segments to extract the *EEG* data in each of the frequency bands. This results in four columns of additional data; *delta* (δ: 0.5 ≤ f ≤ 4 Hz), *theta* (θ: 4 ≤ f ≤ 8 Hz), *alpha* (α: 8 ≤ f ≤ 12 Hz): and *beta* (β: 12 ≤ f ≤ 25 Hz). Finally, all frequency bands in each of the 543 *EEG* segments were normalised to a common scale between zero and one.

3.1.2 Classification

Following an analysis of the literature, the study in this paper adopts simple, yet powerful algorithms. These include the *linear discriminant classifier* (*LDC*), *quadratic discriminant classifier* (*QDC*), *uncorrelated normal density based classifier* (*UDC*), *polynomial classifier* (*POLYC*), *logistic classifier* (*LOGLC*), *k-nearest neighbour*

(*KNNC*), *decision tree* (*TREEC*), *parzen classifier* (*PARZENC*) and the *support vector machine* (*SVC*) (van der Heijde, Duin, de Ridder, & Tax, 2005).

4 Evaluation

4.1 Results Using Top Twenty Uncorrelated Features Ranked Using LDA Backward Search Feature Selection

In this evaluation, the top twenty uncorrelated features, extracted from each of the frequency bands within each of the *EEG* channels, and nine classifiers are used. The performance for each classifier is evaluated using the *sensitivity*, *specificity*, and *AUC* values with 100 simulations and randomly selected training and test sets for each simulation.

4.1.1 Classifier Performance

The first evaluation uses all the *seizure* and *non-seizure* blocks from all subjects in the *CHB-MIT* dataset (171 *seizures* and 171 *non-seizures*). Table 1, shows the mean averages obtained over 100 simulations for the *sensitivity*, *specificity*, and *AUC*.

Table 1: Classifier Performance Results for Top 20 Uncorrelated Features

Classifier	Sensitivity	Specificity	AUC
LDC	70%	83%	54%
QDC	65%	92%	62%
UDC	39%	95%	65%
POLYC	70%	83%	83%
LOGLC	79%	86%	89%
KNNC	84%	85%	91%
TREEC	78%	80%	86%
PARZENC	61%	86%	54%
SVC	79%	86%	88%

As shown in Table 2, the *sensitivities* (*seizure*), in this initial test, are lower for all classifiers. This is interesting given that the number of *seizure* and *non-seizure* blocks is equal. One possible reason for this is that the *ictal* length across the 171 records was 60 seconds. However, in the *CHB-MIT* records *ictal* periods ranged between 6 and 752 seconds. It is possible that some *ictal* blocks resemble *non-seizure* records resulting in misclassification (particularly blocks that contain 6 seconds of *ictal* data).

4.2 Results Using Top Five Uncorrelated Features Ranked Using LDA Backward Search Feature Selection from Five Head Regions

In the second evaluation, the top five uncorrelated features, extracted from five main regions across the head, are used to determine whether the detection of *seizures* can

be improved. Again, the performance for each classifier is evaluated using the *sensitivity*, *specificity*, and *AUC* values with 100 simulations and randomly selected training and test sets for each simulation.

4.2.1 Classifier Performance

As shown in Table 2, the *sensitivities* (*seizure*), for most of the algorithms have improved, including the *specificity* values. The *AUC* results also showed improvements for several of the classifiers, with 93% achieved by the *KNNC* classifier. This is encouraging given that *sensitivities* are more important in this research than *specificities*. From the previous results, we find a 4% increase in *sensitivities*, a 3% increase in *specificities* and a 2 % increase in the performance of the *KNNC* classifier, with other classifiers improving with similar increases.

Table 1. Classifier Performance Results from Top five Uncorrelated Features from Five Head Regions

Classifier	Sensitivity	Specificity	AUC
LDC	78%	88%	55%
QDC	84%	86%	60%
UDC	51%	91%	70%
POLYC	78%	88%	89%
LOGLC	82%	84%	90%
KNNC	88%	88%	93%
TREEC	82%	81%	89%
PARZENC	81%	93%	61%
SVC	85%	86%	90%

5 Discussion

The study in this paper focused on discriminating between *seizure* and *non-seizure* EEG records across a group of 24 subjects, rather than a single individual. The classifiers are trained using all 24 patients, and therefore, classification is generalised across the whole population contained in the *CHB-MIT* database. To achieve this, features from all the channels that capture the *EEG* in all parts of the brain were used. In the initial classification results, the top 20 uncorrelated features from the whole of the head (not region-by-region) were extracted from 805 possible features. This has been accomplished using the *linear discriminant analysis backward search* technique to rank features. This approach achieved reasonably good results, using the *KNNC* classifier, with 84% for *sensitivity*, 85% for *specificity*, 91% for the *AUC*, with a global error of 15%.

Interestingly, the features used in this initial evaluation, involved channels from the four lobes of the brain, *occipital*, *parietal*, *frontal*, and *temporal*, but not the channels spread across the centre of the head. This implied that rather than having generalised

seizures across the whole of the brain, a majority of focal seizures occurred in each of the lobes.

Using the top five uncorrelated features from *EEG* channels specific to the five main regions of the head improved the *sensitivities* and *specificities*, while producing high *AUC* values. The best classification algorithm was again the *KNNC* classifier, which achieved 88% for *sensitivity*, 88% for *specificity,* and an *AUC* value of 93% with a 12% global error. This was followed closely by the *SVC* classifier, which achieved 85% for *sensitivity*, 86% for *specificity,* and an *AUC* value of 90% with a 14% global error.

Generally, this paper produced good results and in many cases better than several papers reported in the literature. Where papers reported better results than ours, a patient-specific seizure detector was used, in contrast to the generalised detector approach taken in this paper. Consequently, it is challenging to make a like-for-like comparison and it is difficult to determine if the higher results produced in our study are, in fact, better than the results produced in patient-specific studies.

6 Conclusions and Future Work

Epilepsy is one of the most common neurological conditions, and one of the least understood. The seizures that characterise epilepsy are frequently unannounced and affect a sufferer's quality of life, as well as increasing the risk of injury or possibly death. A strong body of evidence has suggested that these epileptic seizures can be predicted by analysis of *EEG* recordings.

Within a supervised-learning paradigm, this paper utilises *EEG* signals to classify *seizure* and *non-seizure* records. Most of the previous work in this area has focused on detecting seizures of individual patients, but this paper generalises seizure detection across a group of 24 subjects from the open CHB-MIT database.

A rigorous, methodical, approach to pre-processing of the data was undertaken, and features were extracted from the raw *EEG* signal using several feature-ranking techniques. From our evaluations, the highest result, achieved with the *KNNC* classifier, was 93% for the *AUC*, 88% for *sensitivity*, and 88% for *specificity*.

Despite these encouraging results, more in-depth research is still required. For example, regression analysis, using a larger number of observations would be interesting. This would help to predict the early signs of a seizure, not just when the seizure happens. In addition, more advanced classification algorithms, and techniques, will be considered, including advanced artificial neural network architectures. The investigation and comparison of features, such as *fractal dimension* and *cepstrum analysis*, *autocorrelation zero crossing* and *correlation dimension*, has also not been performed. Future work will investigate these techniques in a head-to-head comparison, with linear methods.

References

1. Aarabi, A., Fazel-Rezai, R., Aghakhani, Y.: A Fuzzy Rule-Based System for Epileptic Seizure Detection in Intracranial EEG. Clinical Neurophysiology 2 120(9), 1648–1657 (2009)
2. Abdul-Latif, A.A., Cosic, I., Kimar, D.K., Polus, B.: Power Changes of EEG Signals Associated With Muscle Fatigue: The Root Mean Square Analysis of EEG Bands. In: IEEE Proceedings of Intelligent Sensors, Sensor Networks and Information Processing Conference, pp. 531–534 (2004)
3. Carney, P.R., Myers, S., Deyer, J.D.: Seizure Prediction: Methods. Epilepsy Behaviour 22, S94–S101 (2011)
4. Diambra, L., De Figueiredo, J.C.B., Malta, C.P.: Epileptic Activity Recognition in EEG Recording. Physica A: Statical Mechanics and its Applications 273(3-4), 495–505 (1999)
5. Engel, J.: Seizures and Epilepsy, p. 736 (2013)
6. Fazel, S., Wolf, A., Langstrom, N., Newton, C.R., Lichtenstein, P.: Premature Mortality in Epilepsy and the Role of Psychiatric Comorbidity: A Total Population Study. The Lancet 382(9905), 1646–1654 (2013)
7. Greene, B.R., Faul, S., Marnane, W.P., Lightbody, G., Korotchikova, I., Boylan, G.B.: A Comparison of Quantitative EEG Features Fro Neonatal Seizure Detection. Clinical Neurophysiology 119(6), 1248–1261 (2008)
8. Iasemidis, L.D.: Epileptic Seizure Prediction and Control. IEEE Transactions on Biomedical Engineering 50(5), 549–558 (2003)
9. Kelly, K.M., Shiau, D.S., Kern, R.T., Chien, J.H., Yang, M.C.K., Yandora, K.A., Sackellares, J.C.: Assessment of a Scalp EEG-Based Automated Seizure Detection System. Clinical Neurophysiology 121(11), 1832–1843 (2010)
10. Libenson, M.: Practical Approach to Electroencephalography, p. 464 (2009)
11. Maiwald, T., Winterhalder, M., Aschenbrenner-Scheibe, R., Voss, H.U., Shulze-Bonhage, A., Timmer, J.: Comparison of Three Nonlinear Seizure Prediction Methods by Means of the Seizure Prediction Characteristic. Physica D: Nonlinear Phenomena 194, 357–368 (2004)
12. Mormann, F., Andrzejak, R.G., Elgar, C.E., Lehnertz, K.: Seizure Prediction the Long and Winding Road. Brain 130, 314–333 (2007)
13. Ning, W., Lyu, M.R.: Exploration of Instantaneous Amplitude and Frequency Features for Epileptic Seizure Prediction. In: 12th IEEE International Conference on Bioinformatics and Bioengineering, pp. 292–297 (2012)
14. Patel, K., Chern-Pin, C., Fau, S., Bleakley, C.J.: Low Power Real-Time Seizure Detection for Ambulatory EEG. In: 3rd International Conference on Pervasive Computing Technologies for Healthcare, pp. 1–7 (2009)
15. Sanei, S., Chambers, J.A.: EEG Signal Processing, p. 312 (2007)
16. Shoeb, A.H.: Application of Machine Learning to Epileptic Seizure Onset and Treatment (2009)
17. Van Der Heijde, F., Duin, R.P.W., De Ridder, D., Tax, D.M.J.: Classification, Parameter Estimation and State Estimation, p. 440 (2005)