

Epileptic EEG detection using the linear prediction error energy

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ABSTRACT

In this study, a method is proposed to detect epileptic seizures over EEG signal. For this purpose, a linear prediction filter is used to observe the presence of spikes and sharp waves on seizure EEG recordings. Linear prediction analysis calculates a coefficient set for each window, which can best model the applied time series signal. Modeling success is observed on the prediction error signal. The presence of spikes and other seizure-specific sharp waves on the signal reduces the modeling success and increases the prediction error of the filter. It is clearly observed that, the energy of prediction error signal during seizures is much higher than that of the seizure free intervals, which indicates the energy value and can be used to locate the seizure interval. The method is applied to 250 distinct EEG records, each of which has 23.6 s duration. The results of the proposed algorithm are evaluated with the ROC analysis which indicates 93.6% success in detecting the presence of seizures. As a conclusion, the linear prediction error energy method can be considered as an efficient way to detect epileptic seizures on EEG records.

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1. Introduction

The basic symptom of epilepsy is recurrent seizing, which can be defined as temporal electrical abnormality of nerves in brain. Seizures can be in different forms such as generalized or focal, which can suddenly affect whole brain or begin in a focus then may spread to other brain areas, respectively. EEG is one of the most common methods in diagnosis and therapy of epilepsy. During epileptic seizures, major changes occur in patient's EEG as a result of excessive synchronous electrical activity of brain. Observation of spikes and sharp waves are some definite characteristics in epileptic EEG (Ropper & Brown, 2005). Detection of seizures on EEG signal recorded for 24 h is required in both diagnostics and therapy which is currently done manually by the neurologist. Today, new methods offered and partially handled in EEG monitoring systems are used to find the seizures on EEG data automatically without spending hours for visual inspection. Some of those methods take into consideration of spectral, statistical or time–frequency properties of EEG signals (Mohseni, Maghsoudi, & Shamsollahi, 2006). Some other methods involve artificial neural networks or decision support systems (Acir, 2005; Adeli, Ghosh-Dastidar, & Dadmehr, 2007; Güler, Ubeyli, & Güler, 2005; Subasi, 2006). Autoregressive models are also used to find the seizure locations by estimating the power spectrum of epileptic EEG signals (Subasi, 2007; Subasi, Ercelebi, Alkan, & Koklukaya, 2006).

EEG signal is an additive result of the cortical electrical activities, generally measured with multi channel recorders. Normal EEG pattern is considered to have a chaotic nature but basic frequency components and specific patterns are known to resemble some certain states of brain, such as deep concentration or sleep stages. A normal EEG is not expected to contain spikes, sharp waves and discontinuities. This type of patterns usually observed when the corrupting effects are added to the signal such as muscle artifacts. Presence of synchronous and almost periodic spikes and sharp waves are the indications of abnormal electrical activity of brain and usually considered as a seizure.

In this study, it is aimed to determine the seizure onset and offset times on EEG signal using error energy of linear prediction (LP) filter. EEG signal is divided into epochs and applied to a linear prediction filter. Optimal coefficients of the filter are calculated to get the best possible model of the signal (Kondoz, 2004). A prediction or modeling error is defined as the difference between the predicted and exact values of the signal. Since the linear prediction has a low-pass nature, presence of spikes on the input signal increases the prediction error (Dandapat & Ray, 1997). The total amount of prediction error for each epoch is calculated and recorded for evaluation of the density of spikes on the signal. It is observed that, the amount of total prediction error of an EEG epoch increases drastically during seizures. A comparison of prediction error with a threshold value is required for the decision of an ictal state onset. The threshold value depends on the number of coefficients of the filter since the modeling capability changes with the number of taps so as the resulting prediction error. In this study,

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a 20 taps LP filter is used. The statistical distribution of prediction errors for previously diagnosed ictal and inter-ictal EEG recordings specifies a threshold value of 300 μV . Since the threshold is a critical decision point, further methods may be offered in specifying its value. In this study, all pre-diagnosed EEG signal epochs are used for design and test purposes and the success of the method is evaluated with a ROC plot. The proposed method has an important contribution to epileptic seizure detection since it is the first application of linear prediction error to define the ictal state EEG. Following sections of this paper are organized as follows. Section 2 explains some properties of EEG recordings and LPC filter application used in this study. Section 3 presents test results from the experiments. Finally, in Section 4, some concluding remarks are given.

2. Materials and methods

2.1. EEG data recordings

Epileptic ictal and inter-ictal EEG recordings required for development and testing of the method were obtained from the EEG database prepared by Andrzejak et al. (2001). Those signals are recorded with a 128-channel 12 bit EEG system with 173.5 samples per second and post-processed with a 0.53–40 Hz band-pass filter. Total 250 distinct recordings each of which has 23.6 s duration are grouped into five categories (A–E). A and B categories are recorded with international 10–20 electrode placement scheme from healthy volunteers at the positions of eyes open and eyes closed, respectively (Fig. 1). C and D categories are inter-ictal recordings from five epileptic patients. Electrodes are placed on epileptic foci for group C and on hippocampus of opposite hemisphere for group D. Recordings of group E are of all seizure activities.

2.2. Ictal stage EEG properties

Epileptic seizure is the abnormal electrical activity that spread over the cerebral cortex. Primary and secondary types are generated in deep brain or epileptic foci, respectively (Wilkinson & Len-

nox, 2005). Spikes and sharp waves in EEG signal are transient high voltage waveform and they might be of an indication of a seizure. On the other hand, the spikes or the sharp waves which occurs inter-ictally in epileptics or in individuals with a genetic disposition to seizures are referred to as epileptiform discharges. These abnormal fast and slow waves may be combined, and when a series of them interrupts relatively normal EEG patterns in a paroxysmal fashion, they are highly suggestive of epilepsy. It is important to note that, between seizures, a single EEG recording may show a normal pattern in as many as 30% of patients with absence seizures and 50% of those with grand mal epilepsy. The records of another 30–40% of epileptics, though abnormal between seizures, are non-specifically so therefore the diagnosis of epilepsy can be made only by the correct interpretation of clinical data in relation to the EEG abnormality (Ropper & Brown, 2005).

Ictal stage EEG has no characteristic form but the presence of abnormalities as spikes and sharp waves are some characteristics during seizure (Ropper & Brown, 2005).

2.3. Epileptic seizure detection with linear predictive filter

A linear predictive filter, estimates the spectral characteristics of the signal window by calculating the coefficients of an FIR filter. This estimation is an optimization process that involves calculation of filter coefficients to achieve the minimum modeling error. By definition, linear predictive filter is an adaptive filter as shown in Fig. 2. In this study, an LPC filter is employed in which the autocorrelation function is used to calculate optimum coefficients. By using LP coefficients, the value of the signal at instant t is predicted from P preceding samples. The difference between predicted and exact values is considered as the modeling or prediction error (Kondoz, 2004).

Mathematical representation of the filter:

$$S' = \sum_{k=1}^P a_k s(n-k) \quad (1)$$

$$e(n) = s(n) - s'(n) \quad (2)$$

$$e(n) = s(n) - \sum_{k=1}^P a_k s(n-k) \quad (3)$$

$$E = \sum_n e^2(n) \quad (4)$$

where $s(n)$, $s'(n)$, $e(n)$, E and a_k are time series signal sample, sample predicted by filter, prediction error between exact and predicted values, total prediction error energy along a signal window and filter coefficients, respectively.

Linear prediction filter assumes that the signal is stationary along the window for which filter coefficients are calculated (Goldberg & Riek, 2000). Filter cannot track sudden changes like spikes and the error energy increases on that instants. Since the linear prediction filter has a low-pass nature, it will not be surprising to have large modeling errors on spike like waveforms. During spikes and transient sharp waves, signal will no longer be stationary

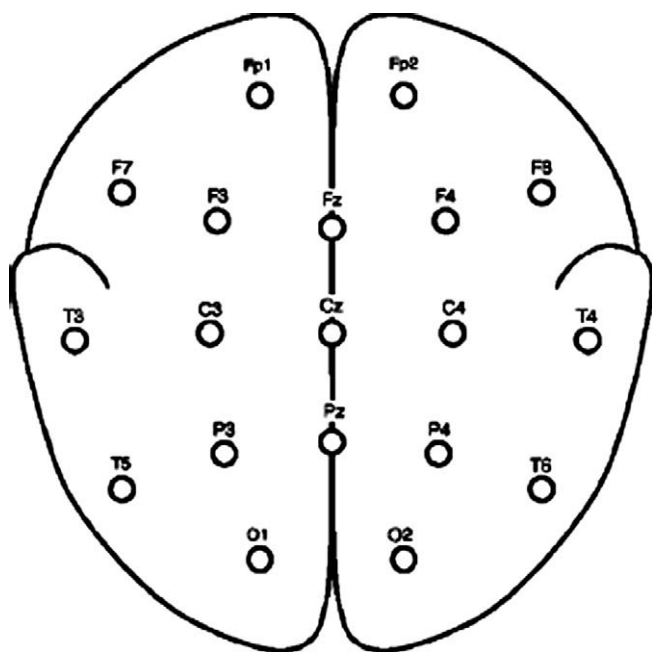


Fig. 1. Standard 10–20 electrode placement scheme for recording EEG signals (Andrzejak et al., 2001).

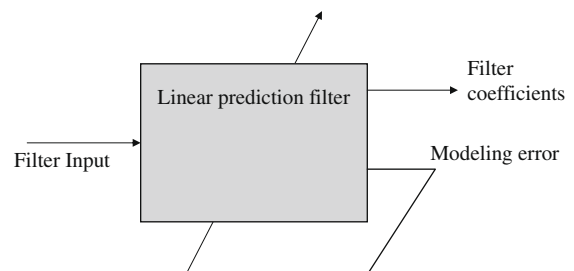


Fig. 2. Linear prediction filter, input/output signals.

resulting in a natural rise of prediction error. EEG signal is not stationary at all but after windowing the signal with sufficient length, it can be considered as “weakly stationary” (Andrzejak et al., 2001).

It is also observed that EEG signal is highly correlated with itself within inter-ictal state compared to seizure intervals (Baier, Müller, Stephani, & Muhle, 2007). This property is also consistent with the change of modeling capability of LP filter during ictal and inter-ictal states.

The EEG recordings used in this work includes 4096 samples and those recordings are also divided into 400 samples long epochs

to provide a weakly stationary behavior. All epochs are applied to the LP analysis by using MATLAB Winterhalder et al. (2006).

LP filter calculates the coefficients for the lowest possible modeling error. The energy of modeling error signal is calculated for each epoch and compared with the threshold value to determine the epileptic state. Error energies higher than threshold value are considered to be ictal state as shown in flowchart in Fig. 3. Two sample recordings under which corresponding modeling error values are plotted are shown in Fig. 4. While average error amplitude for an inter-ictal recording is 55 μV as shown in Fig. 4a, average amplitude for ictal state is 2300 μV as shown in Fig. 4b.

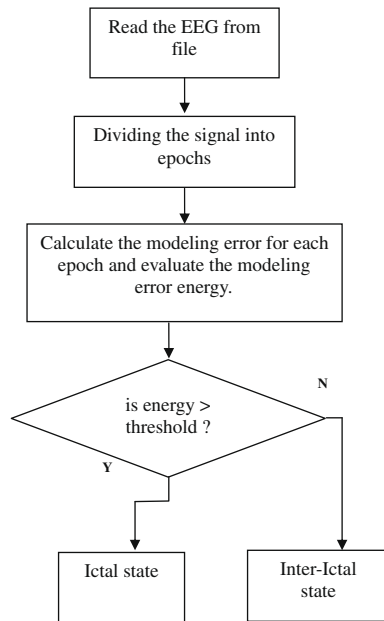


Fig. 3. Flow chart of the proposed method.

2.4. Determination of threshold values

It is a normal situation to observe spikes, namely the epileptiform discharges, on inter-ictal EEG recordings for epileptic patients [1]. To distinguish the ictal onset clearly, the density of presence of spikes must exceed a certain amount, which is considered as a modeling error in this study (Ropper & Brown, 2005). The threshold value for error energy is determined by inspecting the statistical distribution of error energies of both ictal and inter-ictal recordings. The probability distribution plot in Fig. 5a shows that error energies for inter-ictal recordings are accumulated below 300 μV . Whereas Fig. 5b and c show ictal state recording error energies distributed above 300 μV to a higher extend.

3. Results and discussion

Proposed method was tested over 250 recordings each contains 4096 samples. Table 1 summarizes the five categories of recordings and corresponding success rates. The method is applied to both healthy and epileptic subjects to evaluate whether false positive conditions exist or not. When the recordings of healthy subjects were applied to algorithm, overall success of method was obtained as 88% (44/50) for eyes open and 100% for eyes closed situations.

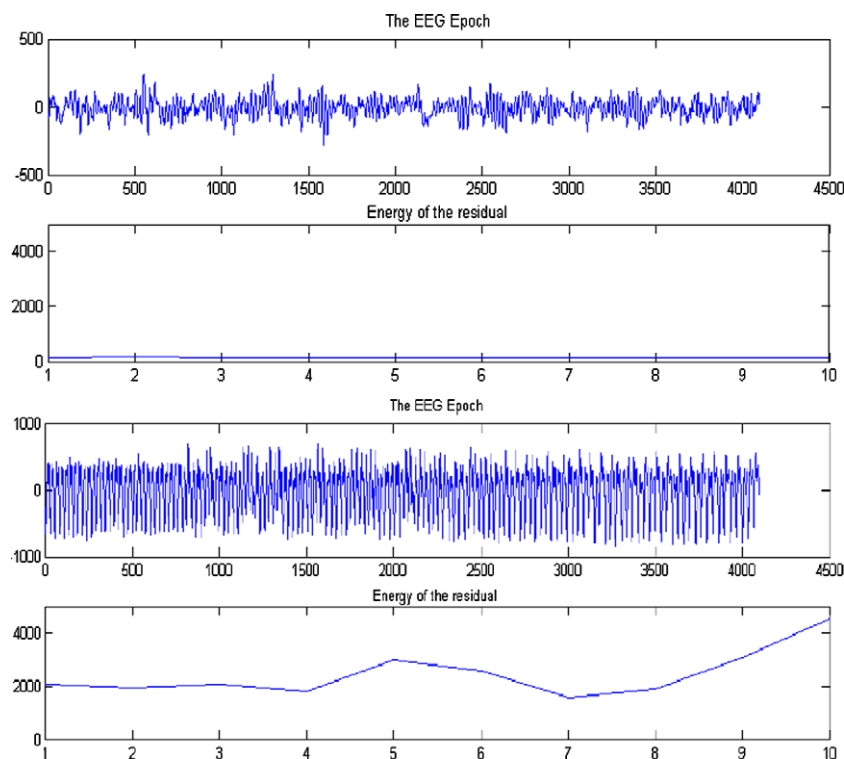


Fig. 4. EEG recordings and corresponding modeling errors. (a) Inter-ictal recording and modeling error, (b) ictal recording and modeling error.

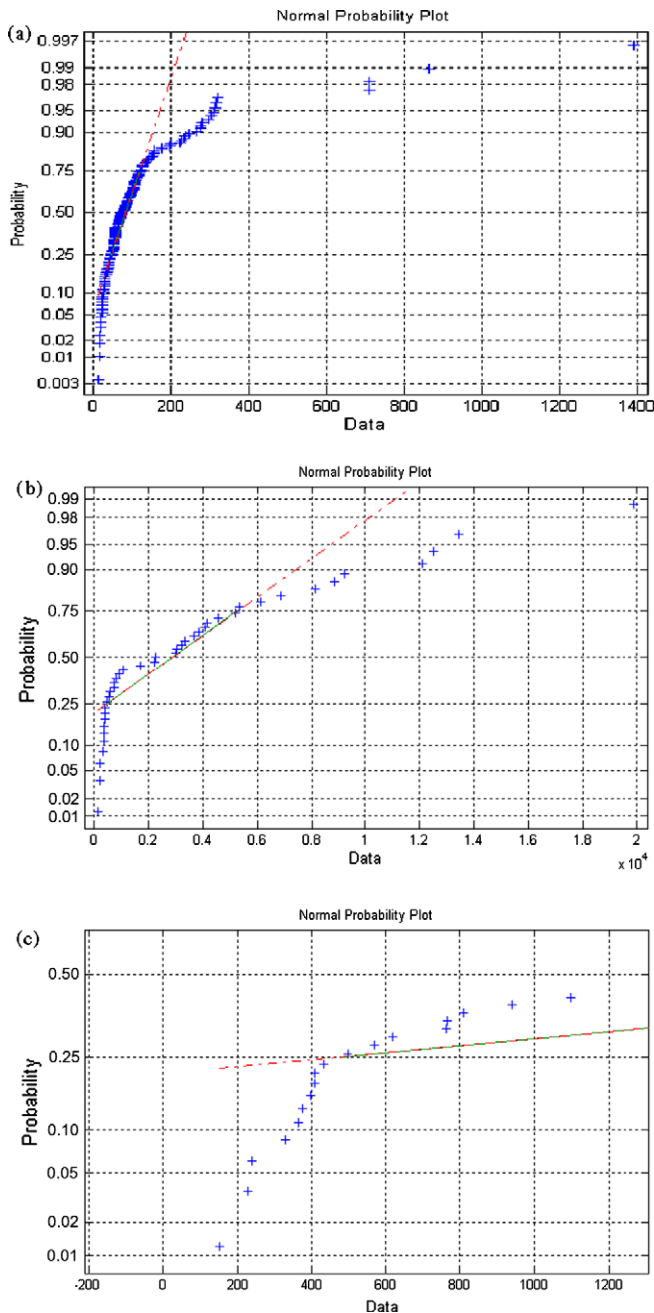


Fig. 5. Error energy distributions (a) inter-ictal (b) ictal (c) zoomed view of ictal distribution around threshold.

Table 1
Recording details and success rates.

Group	Healthy/epileptic	Details	Success
Group A	Healthy normal	Eyes open	44/50 88%
Group B	Healthy normal	Eyes closed	50/50 100%
Group C	Epileptic	Inter-ictal (epileptic focus)	48/50 96%
Group D	Epileptic	Inter-ictal (Hippocam. region)	47/50 94%
Group E	Epileptic	Ictal state	46/50 92%

The open eye healthy volunteer group yielded a respectively lower success rate. Those false positives are considered to be the result of the absence of regular alpha rhythm, which is directly related to the eyes. Open eyes suppress dominant alpha frequencies hence the background noise is modeled by the linear prediction filter rather than the signal itself. This reduces the filter modeling success (Lindsay, Bone, Callander, & Gijn, 1997).

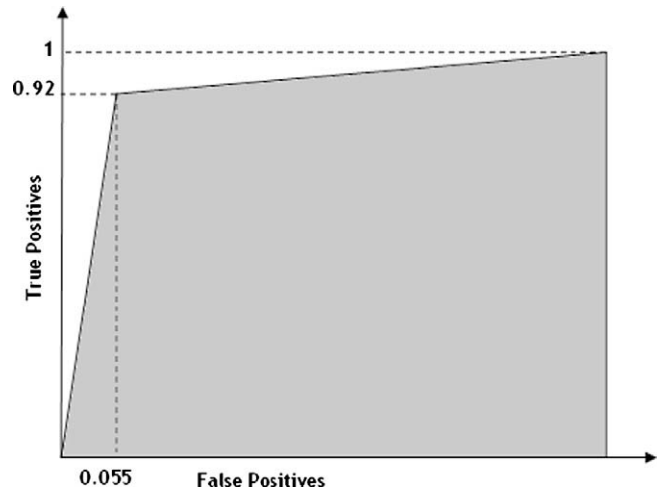


Fig. 6. ROC result.

While inter-ictal recordings are obtained from both hippocampus region and epileptic focus, standard 10–20 placement system is used for ictal state and healthy recordings. Overall success rates for these cases were obtained as 96% (48 of 50) for epileptic focus, 94% (47 of 50) for hippocampus region and 92% (46 of 50) for ictal state as given in Table 1.

We evaluated the performance of the method by using ROC analysis. The ROC reveals overall performance of the detection method independent of any decision boundary. Fig. 6 shows the ROC analysis result of the system. Sensitivity and specificity values for ROC are calculated as follows:

$$\begin{aligned} \text{Sensitivity} &= \text{True Positives} / \text{Total Positives} \\ &= 46/50 \\ &= 0.92 \end{aligned} \quad (5)$$

$$\begin{aligned} \text{Specificity} &= \text{False Positives} / \text{Total Negatives} \\ &= 11/200 \\ &= 0.055 \end{aligned} \quad (6)$$

The resulting success rate is evaluated as the area under ROC in Fig. 6. The large area under ROC indicates that the system may have high sensitivity. Success rate related to sensitivity is computed in Eq. (5) as 0.936 units square. This result confirms experimental results given in Table 1.

4. Conclusions

The results of the study confirm the hypothesis that is the error energy of linear prediction filter can be used as an indicator for the epileptic seizure over EEG recordings. Proposed method may support the efforts of understanding the underlying mechanism of epileptic EEG signal generation and predicting the seizures. This method can also be combined with the other methods such as wavelets, spectral analysis and entropy in order to realize more efficient algorithms. Further developments such as calculating a definite error energy threshold value can also be carried out by using extended EEG data sets, advanced adaptive threshold calculation algorithms and artificial intelligence.

The EEG recordings could not solely diagnose epilepsy, patient stories, seizure witnesses and other imaging modalities are taken into consideration with necessary physical examinations (Wilkinson & Lennox, 2005). Proposed method can be employed as a supporting tool for neurologists to locate seizure onsets in analyzing

24 h EEG recordings, which is applied to almost all epilepsy patients as an essential diagnostic way.

The proposed seizure detection algorithm based on the well-known linear prediction filter does not involve any training phase, which makes it easier to be applied with a high detection rate. This method is considered as an efficient way for detecting epileptic seizures and an inspiration for further developments in this area.

References

- Acir, N. (2005). Automated system for detection of epileptiform patterns in EEG by using a modified RBFN classifier. *Expert Systems with Applications*, 29(2), 455–462.
- Adeli, H., Ghosh-Dastidar, S., & Dadmehr, N. (2007). A Wavelet-Chaos methodology for analysis of EEGs and EEG sub-bands to detect seizure and epilepsy. *IEEE Transactions on Biomedical Engineering*, 54(2), 205–211. doi:10.1109/TBME.2006.886855.
- Andrzejak, R. G., Lehnertz, K., Mormann, F., Rieke, C., David, P., & Elger, C. E. (2001). Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E*, 64, 061907.
- Baier, G., Müller, M., Stephani, U., & Muhle, H. (2007). Characterizing correlation changes of complex pattern transitions: The case of epileptic activity. *Physics Letters A*, 363(4), 290–296.
- Dandapat, S., & Ray, G. C. (1997). Spike detection in biomedical signals using midprediction filter. *Medical and Biological Engineering and Computing*, 35(4), 354–360. PMID:9327612 [PubMed – indexed for MEDLINE].
- Goldberg, R., & Riek, L. (2000). *A practical handbook of speech coders*. USA: CRC Press.
- Güler, N. F., Ubeyli, E. D., & Güler, İ. (2005). Recurrent neural networks employing Lyapunov exponents for EEG signals classification. *Expert Systems with Applications*, 29(3), 506–514.
- Kondoz, A. M. (2004). *Digital speech: Coding for low bitrate communications*. UK: Wiley & Sons.
- Lindsay, K. W., Bone, I., Callander, R., & Gijn, J. V. (1997). *Neurology and neurosurgery illustrated*. UK: Churchill Livingstone.
- Mohseni, H. R., Maghsoudi, A., & Shamsollahi, M. B. (2006). Seizure detection in EEG signals: A comparison of different approaches. *IEEE-EMBC*.
- Ropper, A., & Brown, R. H. (2005). *Principles of neurology* (8th ed.). Boston, USA: McGraw-Hill.
- Subasi, A. (2006). Automatic detection of epileptic seizure using dynamic fuzzy neural networks. *Expert Systems with Applications*, 31(2), 320–328.
- Subasi, A. (2007). Selection of optimal AR spectral estimation method for EEG signals using Cramer-Rao bound. *Computers in Biology and Medicine*, 37, 183–184.
- Subasi, A., Ercelesi, E., Alkan, A., & Koklukaya, E. (2006). Comparison of subspace-based methods with AR parametric methods in epileptic seizure detection. *Computers in Biology and Medicine*, 36(2), 195–208.
- Wilkinson, L., & Lennox, G. (2005). *Essential neurology* (4th ed.). Berlin: Springer.
- Winterhalder, M., Schelter, B., Maiwald, T., Brandt, A., Schad, A., Schulze, B., et al. (2006). “Spatio-temporal patient-individual assessment of synchronization changes for epileptic seizure prediction. *Clinical Neurophysiology*, 117, 2399–2413.