# EEG/SEEG SIGNAL MODELLING USING FREQUENCY AND FRACTAL ANALYSIS

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Abstract: EEG (Electroencephalography) is used to measure the electrical activity of a human brain. It is widely used to analyse both normal and pathological data, because of its very high temporal resolution. Different algorithms were proposed in the literature for EEG signal processing, but a difficult issue is their validation on real signals. An important goal is thus to realistically simulate EEG data. The starting point of this research was the model proposed by Rankine et al. for the surface newborn EEG signal generation. The model, based on both statistical, fractal and classical frequency modelling, has parameters estimated from the real data. A first objective is to validate and parametrize this model on adult surface EEG. A second and more important goal is to parametrize it and to apply it to depth EEG measurements (SEEG). The first results presented in this communication show that the proposed model can be applied in both cases (surface and depth adult EEG), although the parameters are slightly different. As expected, seizures cannot be modelled using this approach.

## 1 INTRODUCTION

Electroencephalography (EEG) is the most widely used method to record electrical activity of the human brain. This data can be used to analyse the behaviour of the normal brain, as well as to diagnose different pathologies, as for example epilepsy. Since our knowledge about the generators of the electrical activity in brain is still on a fairly basic level, most of the signal processing algorithms developed for EEG signals can be validated only by medical expertise. In order to have reliable results, we need to use large datasets for testing. Since EEG recording is time consuming and problematic (because of the high variability of the signals), consistent large data sets are quite difficult to obtain. Simulated realistic datasets would help to build more consistent algorithms and test them more properly.

Depth EEG (called further as SEEG – Stereoelectroencephalography) uses the same principle of electrical activity recording like EEG, but electrodes are surgically inserted into the brain. As expected, because of the invasiveness of the technique, SEEG data is even less frequent than EEG data. Because of their acquisition method, the SEEG signals supposedly directly record brain sources, while the surface EEG is a mixture of source signals. Simulated signal can be useful both for SEEG dedicated studies and for forward/inverse problem applications: with a realistic source modelling, one can expect more realistic scalp EEG modelling. Moreover, in an inverse problem setup, simulated SEEG can be compared to the one obtained by the source estimation algorithms and thus used to validate them.

## 2 EEG MODELS

There are several different approaches to model and simulate EEG signals, depending on the purpose of their applications. The most popular of them are:

- Source modelling from EEG signals (inverse problem, source separation)(Delorme et al., 2007)
- Biological neurocomputing(Robinson et al., 2003; Wendling et al., 2005)
- EEG/SEEG modelling mimicking real signals (Rankine et al., 2008)

Following (Rankine et al., 2008; Stevenson et al., 2005), we focus in this paper on third approach. **Signal imitation** is made using real signal characteristics. Datasets of real EEGs are analysed, in order to obtain these characteristics. Depending on the model,

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different supplementary assumptions are made, and validation is performed against large real datasets.

Rankine et al. separate two models having different characteristics: **seizure model** and **background model**, aiming to characterize different new-born real EEGs (Figs. 1 and 2). We focus here on the (Rank-

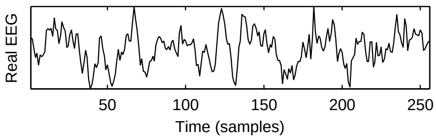



Figure 1: Background EEG signal.

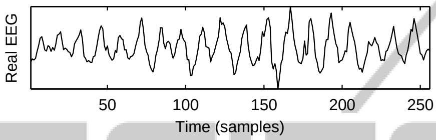



Figure 2: Seizure EEG signal.

ine et al., 2008) background EEG model, our aim being to find if it can be applied on adult surface and depth data. We will asses its validity for both background and seizure signals. The different steps of the cited model and employed methodological tools, are described in more detail in the next section.

## 2.1 Background EEG Modelling

According to (Rankine et al., 2008) and the references cited therein, the power spectrum of a background surface EEG approximately follows a power law:

$$S(f) \approx \frac{c}{|f|^{\gamma}} \tag{1}$$

where $c$ is constant, $f$ is frequency and $\gamma$ is the power law exponent[1]. If one wants to generate a simulated EEG signal $x(t)$, the first step is to express $S(f)$ as $X(f)X^{*}(f)$, with $X(f)$ being the amplitude spectrum of $x(t)$, obtained by the Fourier transform:

$$X(f) = \frac{\sqrt{c}}{|f|^{\frac{\gamma}{2}}} e^{j\theta(f)}, \tag{2}$$

where $\theta(f)$ is the phase of the Fourier transform. In order to obtain a more realistic signal, (Rankine et al., 2008) proposes to generate several $X_i(f)$ using different phase vectors $\theta_i(f)$. Several $x_i(t)$ can be obtained by inverse Fourier transform from $X_i(f)$, and the final simulated background EEG signal is generated as

$$x(t) = \sum_i \mathcal{F}^{-1}(X_i(f)) \tag{3}$$

[1]Since real EEGs are non-stationary, $\gamma$ is considered constant for every epoch of 4 seconds (assuming a quasi-stationary signal during one epoch).

As it can be seen, this model needs three parameters: $c$, $\gamma$ and $\theta(f)$. The amplitude $c$ is of secondary importance, so we will focus only on the last two parameters. In order to use realistic values, they must be extracted from real data.

### 2.1.1 Parameter Estimation

The method used in (Rankine et al., 2008) to estimate the power law exponent $\gamma$ exploits the linear relationship between $\gamma$ and the fractal dimension $FD$ of a signal (Wornell and Oppenheim, 1992), expressed by:

$$FD = \frac{5-\gamma}{2} \tag{4}$$

This step is useful because the $FD$ can be estimated from the real EEGs using one of the fractal dimension estimation methods. Different fractal dimension estimators such as Box-counting, Information and Correlation dimensions (Ott, 2000) can be used, with quite similar results on classical fractals. Higuchi's FD estimation (Higuchi, 1988) is a particular example of fractal dimension derived from box-counting. This algorithm works directly in the time domain (analysing the geometrical form of signal), so it can be used for relatively short signal lengths (recall that EEG's are assumed stationary on short time intervals).

As said previously, in order to simulate realistic signals, the needed parameters ($FD$ and $\theta(f)$) must respect real signals characteristics. As in (Rankine et al., 2008), we have estimated them using the following procedure, applied to a database of real adult background EEG/SEEG signals:

- compute the $FD$ and the phase for each signal
- assume that, over the database, $FD$ follows a beta distribution and estimate the distribution parameters (method of moments (NIST/SEMATECH, 2011)). Probability density function of a beta distribution with two parameters, $\alpha$ and $\beta$ can be expressed as

$$f(x;\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}, \tag{5}$$

  where $x \in [0,1]$ and $\Gamma(z) = \int_0^{\infty} t^{z-1}e^{-t}\mathrm{d}t$ is the $\Gamma$ function.
- assume that the phase $\theta$ follows a uniform distribution in $[-\pi,\pi]$
- test (Kolmogorov-Smirnov) the empirical distributions against theoretical distributions generated using the previously estimated parameters.

#### 2.1.2 Signal Simulation

Assuming that estimated realistic probability distributions have been obtained for both the fractal dimensions $FD$ and for the phases $\theta(f)$, a realistic simulated background EEG can be generated by randomly choosing a value for $FD$ and a phase vector $\theta(f)$ and introducing them in (4),(2) and (3).

In order to validate the approach, (Rankine et al., 2008) suggests to extract $FD$ and $\theta(f)$ from a real EEG measurements and to use the described method to generate a synthetic signal: if the method is correct, then the original signal and the simulated one should be similar (correlated). The correlation index, noted further on as $\rho$, can be computed in time domain ($\rho_t$), as well in frequency (after computing the Welch periodogramm, $\rho_f$) and in time-frequency (spectrograms after short-time Fourier transforms, $\rho_{tf}$).

## 3 RESULTS

The described model was applied to different classes of EEG signals: surface and depth, background and seizure. The database contained 400 signal fragments from 3 different patients, 4 seconds each. Seizure periods were pointed out by neurologists beforehand. Surface EEG signal was filtered with cut-off frequencies at 0.5 and 30Hz whereas source SEEG signal was filtered with low-pass filter at 128Hz (no assumptions on SEEG signal spectral behaviour was made). Consequently, surface EEG signals contained 256 samples and source SEEG signals contained 1024 samples for every 4 seconds window.

### 3.1 Adult Surface EEG

At first, the simulation method was applied to adult surface EEG data. For generality, we tested the model both to background and seizure EEG, downsampled to 64Hz (as in (Rankine et al., 2008)).

The power spectral density (PSD) was computed for several time windows of 4s length, to find out if it exhibitsa power law (1) process behaviour (figure 3). Under this hypothesis, the fractal dimension $FD$ can be estimated using (4).

#### 3.1.1 Parameter Extraction for Background EEG Data

Fractal dimension (thus $\gamma$) and phase spectrum were calculated for every time window from the database and empirical distributions were estimated as described previously. Results are shown in figure 4. $\gamma$ was found to follow a beta distribution with $\alpha = 1.936$ and $\beta = 2.975$. $\theta$ was found to follow uniform distribution in $[-\pi, \pi]$. These hypothesis were confirmed using Kolmogorov-Smirnov test at a 5% significance level.

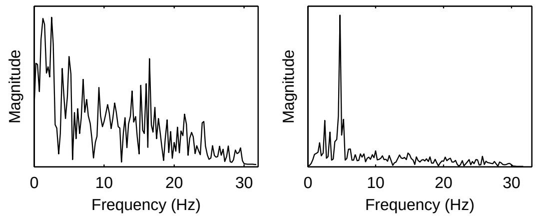
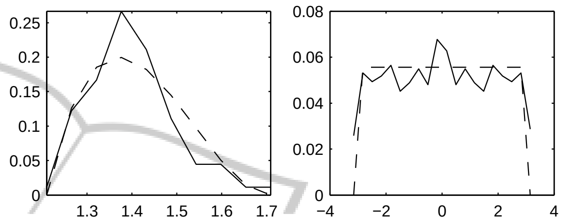



Figure 3: Adult scalp EEG power spectra: background (left) and seizure (right).




(a) $\gamma$ (b) $\theta$

Figure 4: Empirical distributions of the power coefficient $\gamma$ and of the phase $\theta$ for adult scalp background EEG. Theoretical distributions (beta and uniform respectively) are represented by dotted lines.

#### 3.1.2 Parameter Extraction for Seizure EEG Data

The same procedure could be applied also for seizure signals. Still, as seen in Fig. 3, the PSD does not display a power law process behaviour: because of rhythmic seizure activity, a peak in the seizure frequency band might be observed. Consequently, eq. (4) does not hold and other modelling techniques must be applied (see also (Rankine et al., 2008)).

#### 3.1.3 Validation

In order to validate the approach, the second procedure described previously was used: starting from a real signal, $FD$ is estimated and thus $\gamma$. Its phase spectrum was computed ($\theta$) as well as its power (used to estimate $c$). These parameters were used to generate a particular synthetic signal that was later compared with the real one using the validation procedure described previously (3 correlations $\rho_t$, $\rho_f$, $\rho_{tf}$).

**Background EEG.** The obtained modelling results are rather similar between new-born and adult data (see table 1). Adult modelled signals show a better

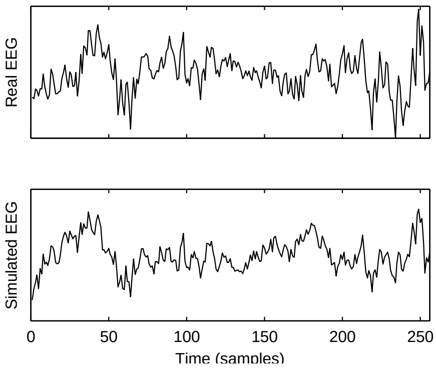



Figure 5: Real and simulated background EEG signals.

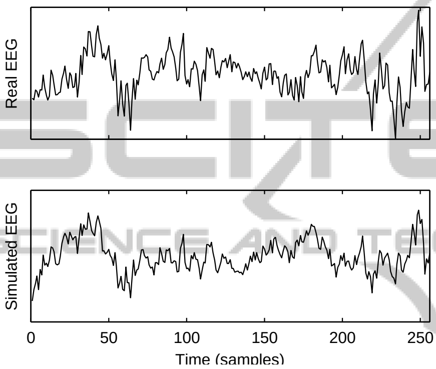



Figure 6: Real and simulated seizure EEG signals.

Table 1: Correlations (mean and sd) for background EEG.

| $\rho$ | new-born (Rankine et al., 2008) | adult |
|---|---|---|
| $\rho_t$ | 0.795 (0.081) | 0.675 (0.075) |
| $\rho_f$ | 0.716 (0.131) | 0.803 (0.150) |
| $\rho_{tf}$ | 0.817 (0.113) | 0.705 (0.075) |

correlation than new-borns in the frequency domain, but correlation in time and time-frequency domains are lower. Globally, it seems that the model proposed for newborns by (Rankine et al., 2008) can be used also for adult surface background EEG modelling.

**Seizure EEG.** Same analysis was performed for seizure EEGs. We compare the correlations of our FD-based model with Rankine's et al.seizure model (developed using a time-frequency approach).

Results from table 2 indicate that, unlike in the previous case, in the time domain this method give better results than (Rankine et al., 2008). On the contrary, in frequency domain correlations are very low. This might be related to the power spectrum density of surface seizure EEG that does not follow power law. Still, due to the high result in the time domain, we think that after an appropriate power spectrum density estimation (i.e. different from $1/f$ process), this model could be used also for adult seizure EEGs.

Table 2: Correlations (mean and sd) for seizure EEG.

| $\rho$ | new-born (Rankine et al., 2008) | adult |
|---|---|---|
| $\rho_t$ | 0.345 (0.176) | 0.661 (0.705) |
| $\rho_f$ | 0.799 (0.093) | 0.494 (0.178) |
| $\rho_{tf}$ | 0.901 (0.056) | 0.680 (0.090) |

## 3.2 Adult Depth EEG (SEEG)

The main difference from a methodological point of view between applying the same approach on EEG and SEEG data is that, since the frequencies contained in the SEEG might be higher, filtering and downsampling are not applied. Examples of power spectra are given Fig. 7.

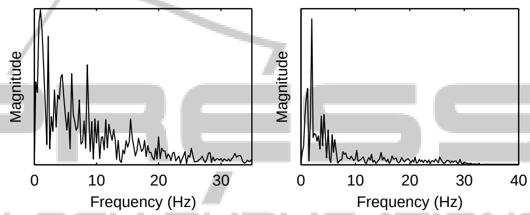
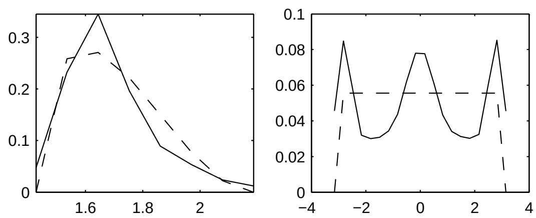



Figure 7: PSD of an adult background (left) and seizure (right) SEEG signal.

### 3.2.1 Parameter Extraction for Background SEEG

Fractal dimension (and thus $\gamma$) and phase spectrum were estimated for every time window. Results are shown in Fig. 8.




(a) $\gamma$ (b) $\theta$

Figure 8: Empirical distributions of the power coefficient $\gamma$ and of the phase $\theta$ for adult depth background SEEG. Theoretical distributions (beta and uniform respectively) are represented by dotted lines.

According to power spectrum density (Fig. 7), we can see that SEEG could be considered as a $1/f$ process. The fractal dimension $\gamma$ distribution was found to follow beta distribution with $\alpha = 1.578$ and $\beta = 2.945$ (note that the values are quite different from the surface EEG). This hypothesis was tested with Kolmogorov-Smirnov test and could not be rejected at the 5% significance level. Meanwhile $\theta$ distribution was not uniform (Fig. 8(b)), so other distributions models should be used to model the phase (Gaussian mixtures for example).

#### 3.2.2 Parameter Extraction for seizure SEEG

The same procedure has been applied also for seizure SEEGs. As expected, the PSD does not display a $1/f$ behaviour, and phase distribution as well is far from the uniform distribution: the described approach is not appropriate for a reasonable simulation of seizure SEEG data.

#### 3.2.3 Validation

**Background SEEG.** As before, for every particular signal of background SEEG a synthetic signal was generated using the extracted parameters.

According to Table 3, the simulated and real signals are moderately correlated (a higher value for the time-frequency correlation though). Still, as shown in Fig. 9, the modelling gives rather visually correct results when compared to real data.

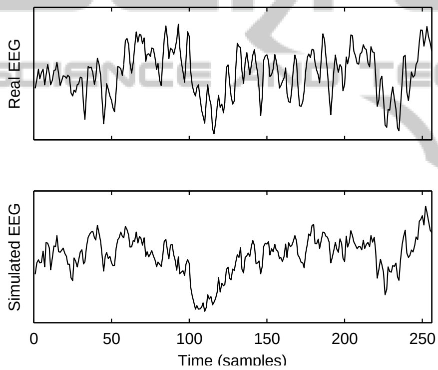



Figure 9: Real and simulated background SEEG signals.

Table 3: Correlation (mean and sd) for background SEEG.

| $\rho$ | adult SEEG |
|---|---|
| $\rho_t$ | 0.587 (0.064) |
| $\rho_f$ | 0.582 (0.201) |
| $\rho_{tf}$ | 0.720 (0.049) |

**Seizure SEEG.** For consciousness, the same procedure was applied for adult SEEG seizures. As expected, the obtained signals show very low correlations results both in time and frequency domains. Again, this is probably due to the specific frequency content of epileptic seizures.

## 4 CONCLUSIONS AND FUTURE RESEARCH

The goal of the research presented in this paper was to explore if an existing model of surface new-born background EEG (Rankine et al., 2008) can be used for adult EEGs (background and seizure, surface and depth). According to our results, it seems that it is possible (although slightly less reliable) to generate an adult background EEG than a newborn EEG. Similarly, it is harder (but possible, mainly if a more realistic phase model is used) to mimic background SEEG signals than surface EEGs. On the contrary, seizure EEG/SEEG signals cannot be reliably generated, probably due to the model assumption on the spectral behaviour ($1/f$).

A first immediate perspective is to confirm the presented findings on a larger database. It might be useful to introduce some categorisation in order to have more specific classes of EEG signals to work with (depending on the actual cerebral activity or on the recording site). Finally, it could be interesting to apply different models for the power spectrum estimation (besides $1/f$, clearly not appropriate for seizure data) and for the phase (not necessarily following a uniform distribution, as seen in the SEEG case).



## REFERENCES

Delorme, A., Sejnowski, T., and Makeig, S. (2007). Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. *NeuroImage*, 34:1443–1449.

Higuchi, T. (1988). Approach to an irregular time series on the basis of the fractal theory. *Physica D: Nonlinear Phenomena*, 31(2):277 – 283.

NIST/SEMATECH (2011). *e-Handbook of Statistical Methods*. Oxford University Press.

Ott, E. (2000). *Chaos in dynamical systems*. Cambridge University Press.

Rankine, L. et al. (2008). A Nonstationary Model of Newborn EEG. *IEEE Transactions on Biomedical Engineering*, 54(1):19–28.

Robinson, P. A. et al. (2003). Neurophysical modeling of brain dynamics. *Physica D: Nonlinear Phenomena*, 28(1):S74 – S79.

Stevenson, N. et al. (2005). Newborn EEG seizure simulation using time–frequency signal synthesis. In *Proc. Workshop Digital Image Computing*.

Wendling, F. et al. (2005). Interictal to ictal transition in human temporal lobe epilepsy: Insights from a computational model of intracerebral EEG. *Clinical Neurophysiology*, 22(2):343–356.

Wornell, G. W. and Oppenheim, A. V. (1992). Estimation of fractal signals from noisy measurements using wavelets. *IEEE Transactions on Signal Processing*, 40(3):611 – 623.