NEWBORN EEG SEIZURE SIMULATION USING TIME–FREQUENCY SIGNAL SYNTHESIS

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Abstract

This paper presents a new method of simulating electroencephalogram (EEG) signals induced by a particular form of newborn seizure. The technique utilises time–frequency signal synthesis. The simulation is based on a nonstationary multicomponent waveform with piecewise linear frequency modulation (LFM). The time–dependent spectral magnitude of the piecewise LFM multicomponent signal is assigned a slowly oscillating envelope and used to construct a time–frequency image. The time–frequency image is used to synthesise a time-domain signal using the modified short–time Fourier transform (MSTFT) magnitude method. The simulated seizures are varied according to several parameters outlined in the literature to provide a large database of EEG seizures. A comparison of the spectrograms of simulated and real seizure results in an average, two–dimensional correlation coefficient of 0.8 (N=5).

1. Introduction

Electroencephalography (EEG) is the study of the electrical activity of the brain using measurements taken from scalp electrodes. It is an important tool in the study of central nervous system (CNS) function, particularly in the newborn. Unlike adult EEG, the signal structure of newborn EEG has high prognostic and diagnostic capability, [1]. In the newborn, EEG is primarily used to identify the existence of seizure. In this instance, the EEG plays a critical role as clinical signs of seizure detection such as muscle spasms, are not clearly present in the newborn as a result of ventilation restraints and anti–convulsive medication. The presence of seizure in newborn EEG indicates neural abnormality which may lead to permanent damage or death.

Normal or background EEG consists of low frequency bursts of activity or irregular random activity. The frequency content of most newborn EEG signals is between 0.4-7.5Hz, [2]. A seizure is defined as an excessive synchronous discharge of neurons within the brain and can last from 10 seconds to upwards of 20 minutes [3, pp. 664].

A class of newborn EEG seizure has been defined, using engineering terminology, as containing linear frequency modulated (LFM) or piecewise LFM signal structures [4]. Seizure may take other forms such as periodic "spiky" behaviour, or repetitive bursts of EEG activity which result in a spectral whitening in the time–frequency domain. However, the goal of this paper is to simulate seizure that exhibits piecewise LFM signal behaviour.

The need for accurate, 24 hour monitoring of newborn EEG has encouraged the development of automated systems to highlight possible periods of interest. Several signals processing techniques, such as correlation, spectral analysis, wavelet transform, matching pursuits and time–frequency distribution based singular value decomposition, have been developed to detect seizure in the newborn, [2, 5, 6, 7, 8]. However, limitations in the training and evaluation data sets have meant that the confidence in the analysis results is reduced and comparisons between techniques are nonexistent. Specific problems with neurologist marked EEG data sets include; a defined level of accuracy, the lack of a publicly available signal database, and the precise localisation of seizure events. A realistic simulation of seizure would permit the comparison of current techniques and provide additional insight into EEG seizure for the next generation of detection techniques [9].

Currently, two models are available to simulate newborn EEG seizure. The first technique developed by Roessgen in [10] is based on some physiological parameters of the brain and utilises a stationary sawtooth waveform. This technique was recently extended by Boashash and Mesbah in [4] to incorporate a single LFM signal. Celka and Colditz have also developed a piecewise LFM model of seizure based on a Weiner filter with sawtooth inputs and nonlinear gain, [9]. The authors outlined a technique to validate their model based on Kullback–Leibler divergence and Renyi entropies, [9].

The Roessgen model lacks the incorporation of non-stationarity, while Boashash's and Mesbah's addition only handles single LFM behaviour, not the piecewise LFM often seen in seizure. Celka's and Colditz's method provides a quality simulation of seizure but lacks time dependent signal shape or time–dependent harmonic magnitude variation. Another difficulty is its inability to simulate the transient, "spiky", activities.

This paper uses the generic piecewise LFM seizure pattern outlined in the work of Boashash and Mesbah, [4], to generate a time–frequency template image which is then synthesised into a time domain signal using the modified short–time Fourier transform (MSTFT) magnitude method, [11].

The advantage of using direct signal synthesis over other techniques is its relative simplicity, its ability to handle spectral distortion and the discontinuities of the piecewise instantaneous frequency (IF) law. In addition, this technique can provide a larger variety of seizure waveforms, within BT product limits (signal richness), [3, pp. 18], depending on the fundamental time–frequency template or templates chosen. This modularity has an advantage over a method such as Celka's which would require additional complexity to incorporate other forms of seizure.

The seizures are randomised by selecting parameter ranges within the limits defined in [4]. Each parameter was assigned according to several user defined beta–distributions. This artifact free seizure simulator can be combined with a background EEG generator to provide a complete newborn EEG simulator.

2. Seizure Simulation

The seizure simulation protocol is outlined is Figure 1.

Initially, the desired seizure length is determined. The parameters for the seizure are chosen from their specific sampling distribution. These parameters include the number of LFMs in the IF law, the slope of the LFMs, the seizure start frequency, the envelope of each harmonic component (relative amplitude and frequency), the signal to noise ratio (SNR) and seizure to background ratio (SBR). The parameter range and parameter sampling distribution are specified in Table 1. Note, the beta distribution ranges from 0 to 1 so the range is used to correctly scale the sampling distribution.

The initial IF law is generated from the selected param-

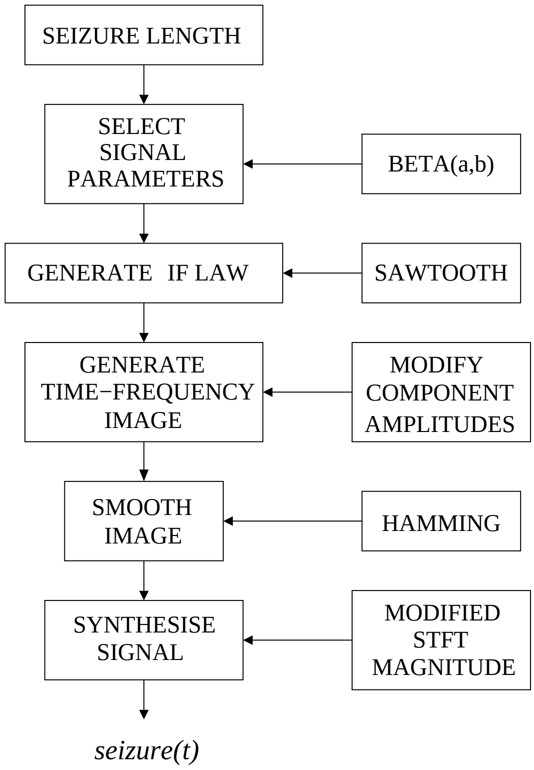


Figure 1. Block diagram of seizure simulation.

Table 1. Parameter ranges and distribution

parameter	range	distribution
LFM slope (Hz/sec)	-0.07:0.07	Beta(2,4)
LFM number	1:4	Beta(3,3)
LFM envelope amplitude	-0.25:0.25	Beta(1,1)
SNR (dB)	3:20	Beta(1,1)
SBR (db)	10:20	Beta(1,1)
seizure start frequency (Hz)	0.5:3.5	Beta(2,4)

eters according to,

$$f(t) = \sum_{i=1}^{N} a_i t_i + c_i, \tag{1}$$

where,

$$t_i = \begin{cases} 0 & \text{for } t < t^i_{\text{lo}}, \\ t & \text{for } t^i_{\text{lo}} \leq t \leq t^i_{\text{hi}}, \\ 0 & \text{for } t > t^i_{\text{hi}}, \end{cases} \tag{2}$$

where $f_i(t)$ is the IF law, a_i is the slope of the i^{th} LFM monocomponent, c_i is a constant to correctly align the pieces of the IF law, N is the number pieces in the piecewise LFM and t^i_{lo} and t^i_{hi} are random variables with t^i_{hi} conditioned on t^i_{lo} such that $t^i_{\text{hi}} > t^i_{\text{lo}}$.

The time–frequency image is initially constructed, using the IF law, with the harmonic relationship of a sawtooth waveform (1 at fundamental, $1/2$ at first harmonic and $1/\sqrt{8}$ at second harmonic, etc). The magnitude of each harmonic component is multiplied by a specific, oscillating, random amplitude envelope that is estimated using cubic spline interpolation ($f_{\mathrm{envelope}}(t) << f(t)$). The time–frequency image is smoothed, along the frequency axis, using a one–dimensional Hamming window that is scaled according to the seizure length. The two–dimensional, time–frequency image is then synthesised into a one-dimensional, time domain signal using the MSTFT magnitude method assuming a sampling frequency of 10Hz.

The MSTFT magnitude method uses an iterative technique developed by Griffin and Lim, [11], to estimate the discrete time–domain signal $x[n]$. The difference between the desired STFT and the update STFT is minimised in this procedure. The update equation is as follows,

$$x_{i+1}[n] = \frac{\sum_{m=-\infty}^{\infty} w[n-m] \int_{-0.5}^{0.5} \hat{X}_i[n,f] e^{j2\pi fm}\, df}{\sum_{m=-\infty}^{\infty} w^2[n-m]} \tag{3}$$

where,

$$\hat{X}_i[n,f) = |Y[n,f)| \frac{X_i[n,f)}{|X_i[n,f)|}, \tag{4}$$

$Y[n,f)$ is the desired STFT, $X_i[n,f)$ is the i^{th} update STFT, $x_i[n]$ is the i^{th} update synthesised signal, $w[n-m]$ is the STFT window, n is discrete time, f is continuous frequency and m is the discrete time lag. The signal is synthesised with an initial $x[n]$ of white Gaussian noise. In this case the stopping criteria of the MSTFT magnitude method is the iteration number ($i_{\max} = 200$). Further details on the convergence of the algorithm can be found in [11].

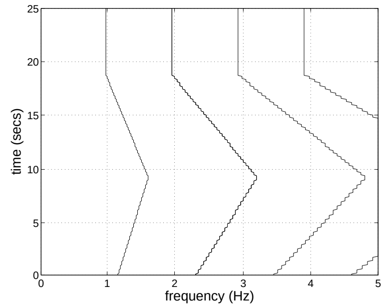
This method of signal synthesis was chosen over other available techniques as the signal synthesis is performed on a much simpler image than other techniques, which require the incorporation of cross–terms in the original image, and no knowledge of the phase is required.

Once the signal is synthesised white Gaussian noise (sensor error) and residual background EEG can be added to the signal.

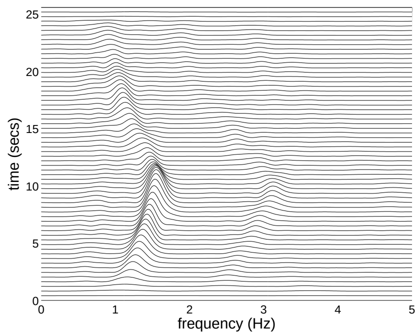
3. Results and Discussion

The data used in the following results were collected from the Royal Women's Hospital Perinatal Intensive Care Unit in Brisbane, Australia. The data were recorded, using a sampling frequency of 256Hz and local electrode referencing, by a Medelec machine. The signals were then down sampled to 10 Hz for further processing.

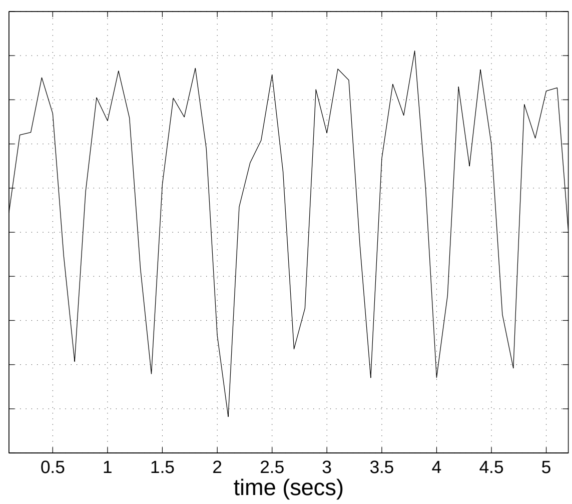
A typical output of the piecewise LFM, EEG seizure simulation algorithm is shown in Figure 2. The component



(a) generate IF law



(b) create time–frequency image



(c) synthesised seizure

Figure 2. The seizure synthesis procedure.

IF laws are shown in 2a), the simulated EEG seizure time–frequency image is shown in 2b) and the synthesised seizure signal with this time–frequency characteristic is shown in

2c). It can be seen that the simulated EEG seizure exhibits similar traits of real EEG seizure data as shown in Figure 3.

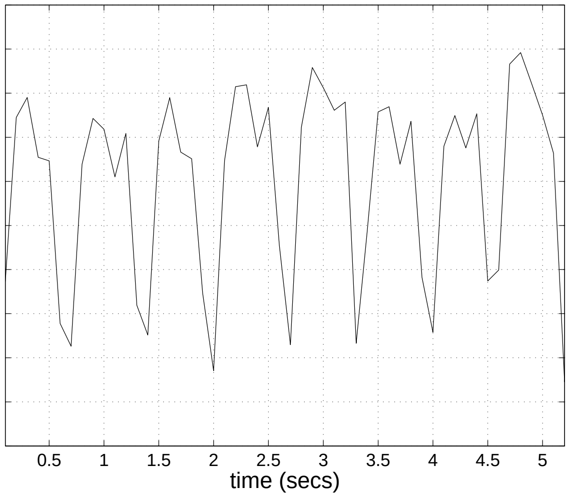


Figure 3. A newborn EEG seizure epoch.

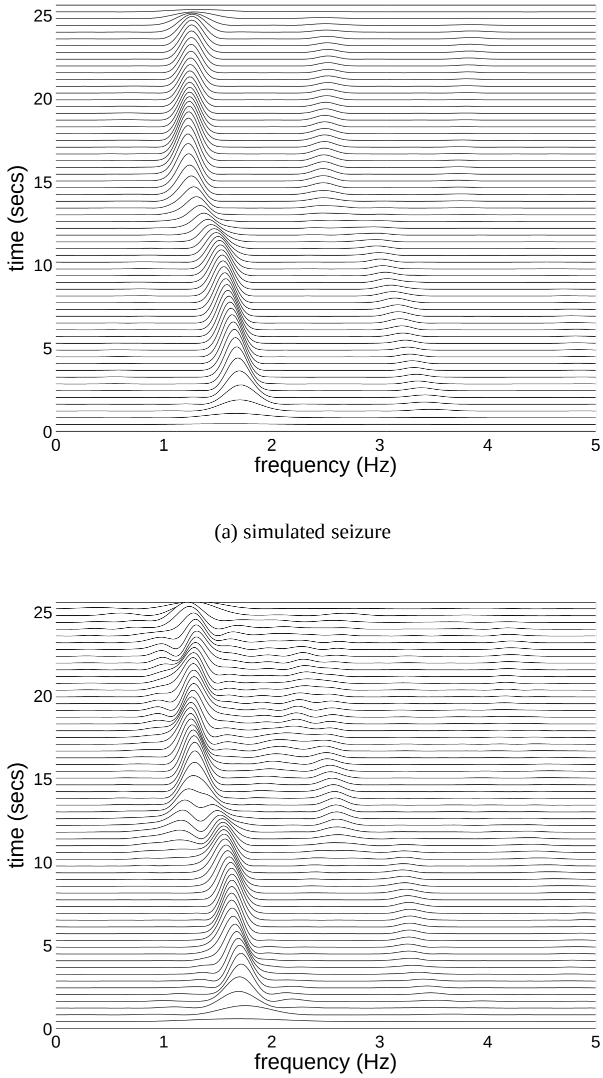
For a more quantitative analysis, select segments of real EEG seizure were analyzed with the intention of extracting an approximation to the piecewise LFM law and the component envelope. These values were then fed into the seizure simulation algorithm and the time–frequency images were then correlated to assess the similarity between simulated and real seizure. The results of this experiment, conducted on five seizure epochs, are shown in Table 2.

Table 2. The results of the seizure simulation technique, $\mu = 0.8,\ \sigma^2 = 0.03$**.**

trial	correlation
1	0.861
2	0.920
3	0.943
4	0.486
5	0.789

An example of the time–frequency output of the experiment is shown in Figure 4. The synthesised seizure is plotted above the real seizure in Figure 5. The general shape of the simulated time–frequency image conforms to the seizure epoch with a correlation coefficient of 0.94. In the time domain the signal has the general characteristics required of a simulated signal, [4, 9], notably, nonstationary frequency content, moderate "spiky" behaviour, asymmetric oscillation and envelope amplitude variation.

The simulated EEG is not exact, but it provides the essential signal structures seen in EEG seizure, particularly in the time–frequency domain, as outlined in [4]. This is



(a) simulated seizure

(b) real seizure

Figure 4. Time–frequency domain comparison of real and simulated seizure, $\rho = 0.94$**.**

shown in the high two–dimensional correlation coefficients between real and simulated signals. However, not all forms of seizure fit into this general piecewise LFM pattern of behaviour. This can be seen by the low coefficients in trial 4. This particular form of seizure has a higher relative noise component, a non–piecewise LFM IF law, more transient events and contains severe "spiky" behaviour compared to other seizures. These phenomenon contribute to an effective whitening of the spectrum which interferes with the simulative capacity of a piecewise LFM model. Nonetheless, the synthesised seizure still has sections that provide a good

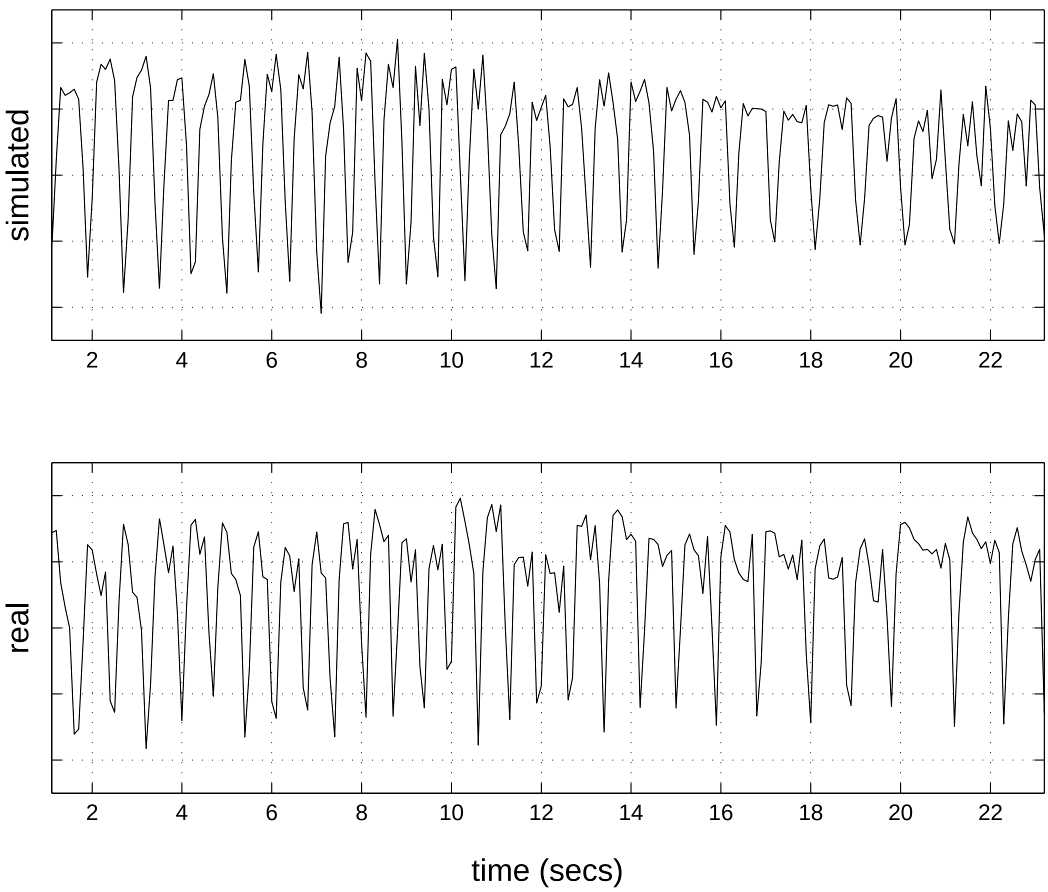


Figure 5. Time–domain comparison of real and simulated seizure.

approximation, in addition to poor approximation sections. This can be seen in Figure 6.

These forms of error can be overcome by using additional time–frequency templates to cater for transient (time–dependent spectral whitening), and low SNR and SBR (a spectral whitening or colouration, of the time–frequency domain, respectively) effects.

The incorporation of a background model such as that outlined in [12] and a suitable artifact simulator into this seizure model can provide a EEG signal simulator that is capable of providing realistic EEG signals. In the case of multichannel EEG, where a seizure is not sensed equally at each electrode, this technique can be expanded by adding a channel model (stationary or nonstationary), variable amplitude background signals, and channel delays. A fully operational newborn EEG simulator will permit the evaluation of the myriad of signal processing techniques currently available to the problem of automatic seizure detection in newborn EEG. Such a system is outlined in Figure 7.

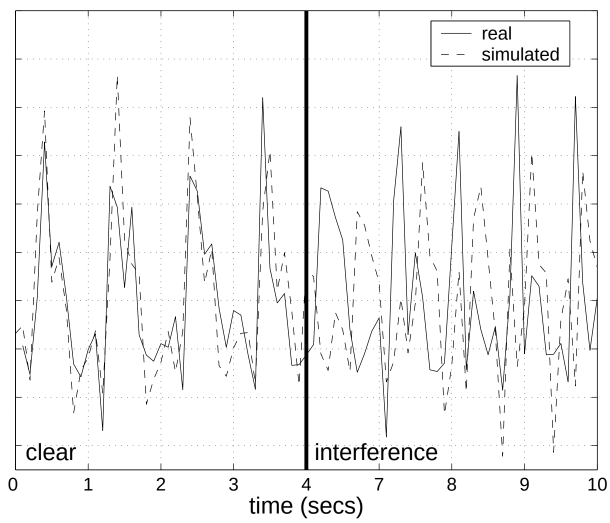


Figure 6. Simulated and real seizure.

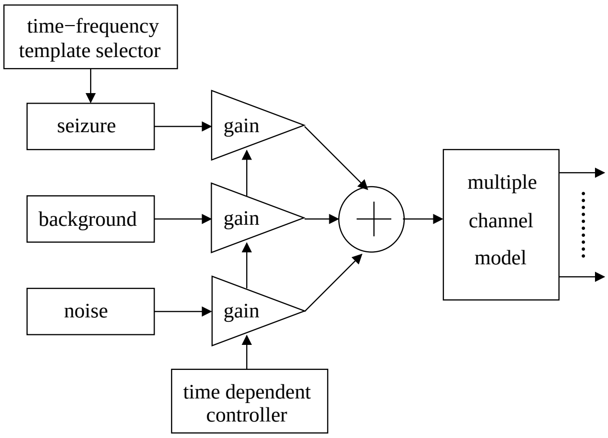


Figure 7. Complete newborn EEG simulator.

4. Conclusion

A method of neonatal EEG simulation using time–frequency signal synthesis has been developed. The technique uses the randomised selection of the piecewise LFM signal model proposed by Boashash and Mesbah in [4]. Examples of the simulation routine have shown high correlation with select seizure periods $(\rho = 0.8,\ N = 5)$. The simulation can also provide approximation of seizures with moderate "spiky" behaviour. It cannot provide quality simulation for seizure epochs with low SNR/SBR or high power transients (non–piecewise LFM data). The randomisation permits the simulation of a large set of possible seizure. Such a simulation method allows for a consistent data set to compare several currently available seizure detection techniques.

5. Acknowledgments

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