# NEWBORN EEG SEIZURE DETECTION USING SIGNAL STRUCTURAL COMPLEXITY

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## ABSTRACT

A method for the automatic detection of seizure in newborns is presented. The proposed method is derived from the ability to detect changes in signal structure as the newborn EEG changes from the background state to the seizure state. Matching Pursuit decomposition technique, with an overcomplete time-frequency dictionary, is shown to be an adequate technique for detecting changes in signal structure. Changes are detected by using a new signal measure referred to as structural complexity, which is directly related to the dictionary being used for decomposition. The structural complexity measured is then incorporated in the proposed automatic newborn seizure detection algorithm.

## 1. INTRODUCTION

Atomic decomposition can be used to represent or approximate a signal as a linear superposition of weighted dictionary atoms. If the dictionary used for the linear expansion is an orthogonal basis, such as the Fourier or wavelet bases, then it will not have the ability to provide a good representation for a wide range of signal structures that are highly localized in time and frequency. For example, the discrete Fourier transform cannot provide a good representation of signal components that have short time durations (i.e. localized in time) and wavelet bases provide poor resolution for narrow band, high frequency components [1]. The use of highly redundant, overcomplete dictionaries leads to multiple possible representations of a given signal. The benefit of using overcomplete time-frequency and/or time-scale dictionaries is that the representation can adapt to localized time-frequency structures.

Matching pursuit (MP) is one atomic decomposition method that can provide a signal representation using an overcomplete time-frequency dictionary [1]. The MP algorithm is fast becoming a popular alternative to classical signal representation. The ability of MP to adapt to localized signal structures makes it is a suitable technique for the representation of non-stationary signals such as the newborn electroencephalogram (EEG) [2]. This indicates that MP, with a redundant time-frequency dictionary, is suitable for use in an automatic newborn seizure detection algorithm.

Seizures occur more frequently in newborns than in any other period of life and are the most prominent sign of central nervous system abnormalities in the neonate. Approximate rates of seizure in newborns have been given in the range of 0.15% to 0.55% [3]. Seizures create instant concern about the possible cause of the brain disorder as well as the effects seizures may have on the developing brain.

It is believed that in normal brain activity, neurons within the brain fire randomly. This activity becomes more organized and neurons discharge synchronously in the case of seizure. Newborn EEG seizure is characterized by rhythmic [4] or sharp repetitive waveforms [5] which distinguishes itself from the general lack of pattern or structure [3] of the EEG signal observed during non-seizure periods.

Previous non-parametric methods of newborn seizure detection have been categorized into time, frequency, time-scale and time-frequency domain based algorithms [6, 4, 7, 2]. The MP algorithm, along with a redundant time-frequency dictionary, provides a time-frequency signal processing technique that can facilitate the non-stationarities that are present in the newborn EEG signal [2].

In this paper we show, using the MP algorithm, that we can detect a change in signal structure when a signal becomes more or less coherent with the decomposition dictionary. A signal measure, referred to as structural complexity, is firstly defined. This measure is related to the notion of sparsity or number of significant atoms in a representation and strongly depends on the nature of the atoms in the dictionary being used for decomposition. Structural complexity is then shown to be capable of distinguishing between seizure and non-seizure periods in the newborn EEG.

## 2. MP DECOMPOSITION

Atomic decomposition methods are used to represent or approximate signals as linear superpositions of weighted atoms from the dictionary used in the decomposition. The selected atoms, $\phi_\gamma$, are chosen from a dictionary $\Phi = \{\phi_\gamma\}_{\gamma\in\Gamma}$, with $\gamma$ being a parameter or set of parameters that uniquely defines each individual atom in the dictionary. Examples of these parameters are used, for example, to create the Gabor dictionary which consists of translated, scaled and modulated versions of a Gaussian window $\phi(t)$ such that

$$\phi_\gamma(t) = \frac{1}{\sqrt{s}}\phi(\frac{t-\mu}{s})e^{i\xi t}$$

where $\gamma = (s, \mu, \xi)$. The representation of signal $f$ is given as

$$f = \sum_{\gamma\in\Gamma} \alpha_\gamma \phi_\gamma$$

where $\alpha_\gamma$ is the coefficient associated with the atom $\phi_\gamma$. The signal $f$ can be approximated using $m$ atoms by

$$\hat{f} = \sum_{i=0}^{m-1} \alpha_{\gamma i}\phi_{\gamma i} \quad (1)$$

The representation error $R^m f = f - \hat{f}$ is referred to as the residual [1].

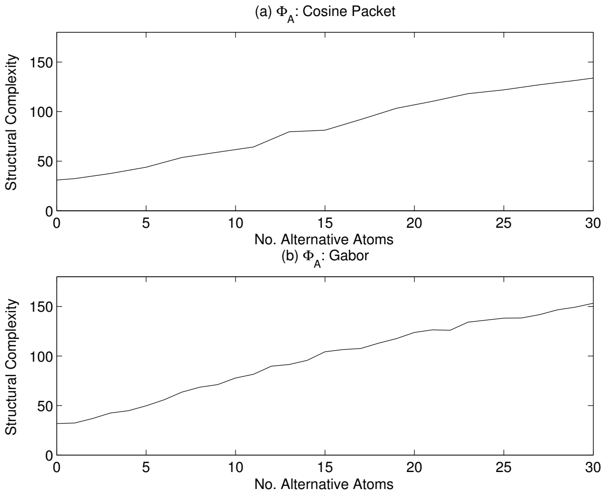


Figure 1: The structural complexity levels of synthetic signals when using (a) cosine packet dictionary and (b) Gabor dictionary as the alternative dictionary $\Phi_A$.

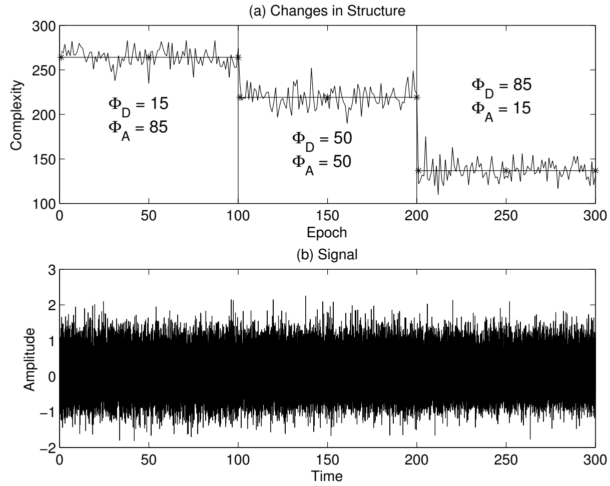


Figure 2: Shows the (a) significant change in structural complexity when the structure in the (b) signal change

From the multiple possible representations using an overcomplete dictionary, the MP algorithm provides one. It does so by enforcing a set of rules associated with specific objectives. MP is an iterative algorithm in which the objective is to select the atom $\phi_{\gamma i}$ at each iteration that has the largest inner product with the residual (n.b. $R^0 f = f$). The coefficient $\alpha_{\gamma i}$ takes the value of the inner product $\langle R^i f, \phi_{\gamma i}\rangle$ when the dictionary $\Phi$ has been normalized so that each atom $\phi_\gamma$ has the same $\ell^2$ norm. For our dictionaries $||\phi_\gamma||_2 = 1\ \forall\gamma$. A representation using the MP algorithm can then be given as

$$\begin{aligned} f &= \sum_{i=0}^{m-1} \langle R^i f, \phi_{\gamma i}\rangle \phi_{\gamma i} + R^m f \\ &= \hat{f} - e_a \end{aligned}$$

where $e_a = -R^m f$ is the approximation error.

## 3. STRUCTURAL COMPLEXITY

The structural complexity measure is based on a method for determining significant atoms from MP decomposition. In an MP decomposition the significant atoms are those atoms chosen to represent the signal based on predefined criteria. We note that a signal to error ratio (*SER*) in decibels given by

$$SER = 10\log_{10}\left(\frac{E_f}{E_{e_a}}\right) \quad (2)$$

can be defined given a signal approximation using $m$ atoms from $m$ iterations of the MP algorithm (see (1)). A stopping criterion based on a desired level of $SER$ ($SER_D$) can be defined for MP. The MP iterations continue until $SER \geq SER_D$ [8]. Note that $E_f$ and $E_{e_a}$ in (2) are the energy in $f$ and $e_a$ respectively.

Coherent structures were defined in [1] as signal components that have a strong correlation with dictionary atoms. It should be noted that the number of atoms needed to represent a signal with structures that are coherent with the decomposition dictionary would be less than with a dictionary that is not coherent with the signal structures. Therefore we introduce the measure of structural complexity to be the number of atoms needed by MP to approximate a signal to a specified $SER$ in conjunction with the dictionary being used for decomposition.

Figure 1 shows how the structural complexity measure changes for signals with varying levels of coherency with the decomposition dictionary. This was achieved by constructing signals using atoms from two different dictionaries. One dictionary will be referred to as the decomposition dictionary, $\Phi_D$, as it will be the dictionary used by the MP algorithm for decomposition. The other dictionary will be referred to as the alternative dictionary, $\Phi_A$. Using varying numbers of atoms from $\Phi_D$ and $\Phi_A$, we can construct signals with varying levels of structural complexity.

The synthetic signals are constructed using $k$ randomly selected atoms of which $k-l$ atoms are selected from $\Phi_D$ and $l$ from $\Phi_A$. $l$ is then increased from 0 to $k$ in a number of steps. In the presented results we have chosen $k = 30$ and $\Phi_D$ as the overcomplete wavelet packet dictionary.

It was expected that as $l$ increased so too would the level of structural complexity. This is because more atoms from $\Phi_A$ were being used for signal construction and the signals became less coherent with $\Phi_D$. All atoms used in constructing the signals, whether they were from $\Phi_D$ or $\Phi_A$ were normalized so that their $\ell^2$ norm was equal to one. For each value of $l$, twenty five realizations were obtained so that an average number of atoms needed to approximate the signal could be calculated. The MP approximations were chosen such that the desired $SER$ is 15dB.

In Figures 1a and 1b we have used an overcomplete cosine packet and overcomplete Gabor dictionary as $\Phi_A$ respectively. In both Figures 1a and 1b it can be seen that as the signals are constructed with more $\Phi_A$ atoms and less $\Phi_D$ atoms the level of structural complexity increases.

Figure 2 is a synthetic example of how the structural complexity measure can detect a change in signal structure. The synthetic epochs were created using 100 atoms from the wavelet packet dictionary, $\Phi_D$ and the cosine packet dictionary, $\Phi_A$. The synthesized epochs were created with atoms randomly selected from $\Phi_D$ and $\Phi_A$. Three types of epochs with three levels of coherency with the $\Phi_D$ were created such that

- Epochs 1 $\rightarrow$ 100: $\Phi_D = 15$ & $\Phi_A = 85$
- Epochs 101 $\rightarrow$ 200: $\Phi_D = 50$ & $\Phi_A = 50$
- Epochs 201 $\rightarrow$ 300: $\Phi_D = 85$ & $\Phi_A = 15$

Figure 2a indicates exactly when there is a change in the structures that form the signal in Figure 2b. The entire signal is the concatenation of the synthesized epochs.

The above results show that MP, using the structural complexity measure, can indicate a change in signal structure when the structures in the signal change so that they become more or less coherent with $\Phi_D$. That is, if the structures in the signal become less coherent with $\Phi_D$, an increase in the structural complexity will result. A decrease in the structural complexity occurs when the signal structures become more coherent with $\Phi_D$.

## 4. NEWBORN EEG ANALYSIS USING STRUCTURAL COMPLEXITY

The newborn EEG signals analyzed in this paper were all recorded at the Royal Children's Hospital, in Brisbane, Australia. Fourteen electrodes placed according to the international 10-20 standard of electrode placement allowed for twenty channels to be recorded using the bipolar derivation method. The recording was done using the Medelec system with a sampling frequency of $F_s$ = 256Hz. A notch filter at 50Hz was applied to remove any AC line artefacts.

The EEG recordings were partitioned into epochs of length 2048 samples. The stopping criterion for the MP algorithm was $SER \geq SER_D$ = 13dB. A dictionary that would be coherent with newborn seizure was desired as we believed this would result in a drop in structural complexity when the EEG changed from the background state to the seizure state. It has previously been observed that the newborn EEG seizure are rhythmic in nature [4] and this was confirmed in our initial analysis of the EEG in our database. Therefore a cosine packet dictionary was chosen to be used by MP in the decomposition. The newborn EEG seizure has also been demonstrated to exhibit time-varying linear FM like components [2]. Therefore a cosine packet dictionary would be much more suited to this type of signal than a Fourier dictionary due to the non-stationarity.

In analyzing the non-seizure recordings with the structural complexity measure, using the cosine packet dictionary, it was found that the non-seizure periods contained relatively constant levels of structural complexity. This is shown in Figure 3a, which corresponds to the complexity levels of the newborn EEG in Figure 3b.

Most of the severe short-term fluctuations that occur during non-seizure and seizure periods are an effect from some form of artefact with significant amplitude. Large amplitude artefacts can be in the form of spikes or slow waves. Both generally cause a reduction in the structural complexity measure. This can be seen particularly in the non-seizure section of Figure 4 where the normally constant non-seizure EEG complexity levels have a number of sharp drops. However, with low pass filtering to smooth the structural complexity time series, these short sharp fluctuations can be reduced and a clear distinction between seizure and non-seizure can still be observed (see Figure 4). This is a post-processing method

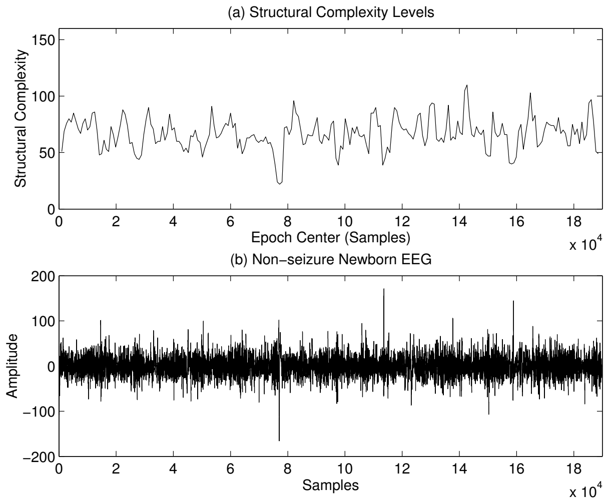


Figure 3: (a) Shows the structural complexity levels associated with the (b) non-seizure newborn EEG

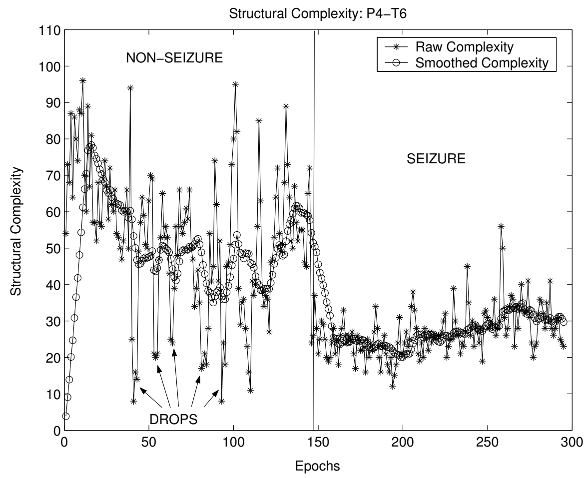


Figure 4: Non-seizure and seizure structural complexity results in raw and smoothed form from channel P4-T6.

which reduces the affect large amplitude artefacts have on the structural complexity measure.

There were, however, a number of seizures that did not correspond to low structural complexity levels when using the cosine packet dictionary for decomposition. Instead we found a significant increase in the structural complexity as is shown in Figure 5. However, we can still distinguish this type of seizure from non-seizure sections using the structural complexity measure.

Further analysis of the EEG signals gave insight to the reasons for various structural complexity levels for differing patterns in newborn seizure. A typical epoch associated with low complexity is given in Figure 6a and the usual seizure epoch associated with high complexity is shown in Figure 6b. The high energy low frequency rhythmic pattern in Figure 6a is easily represented by a small number of cosine packet dictionary elements, which results in a low structural complexity level. However the epoch in Figure 6b has an even spread of energy over a wider range of frequencies and therefore a large number of atoms in its representation (i.e. high struc-

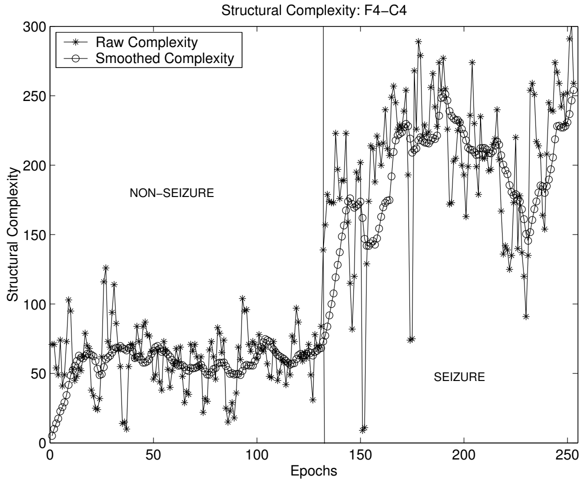


Figure 5: Non-seizure and seizure structural complexity results in raw and smoothed form from channel F4-C4.

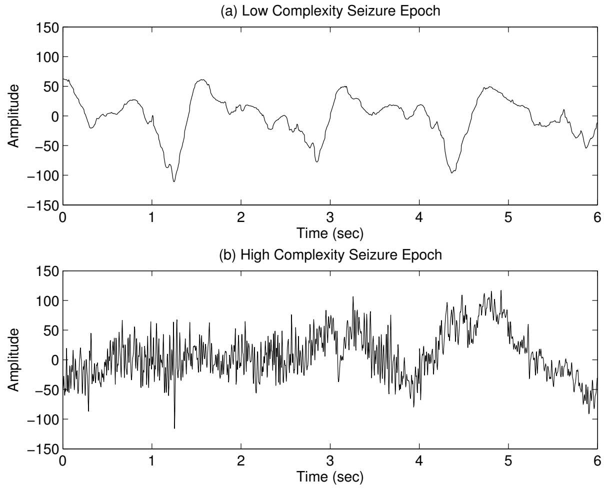


Figure 6: Typical seizure epochs associated with (a) low structural complexity and (b) high structural complexity

tural complexity).

## 5. EEG SEIZURE DETECTION

A sliding window of 2048 samples with an overlap of 60% was used on all twenty available channels from the newborn recordings. The structural complexity value was calculated for each epoch after the epoch had been high pass filtered with a cutoff frequency at $F_h = 0.3$Hz. The high pass filter removed any DC components along with insignifcant low frequencies [9]. The structural complexity results were then treated as a time series and were fed into a lowpass filter to smooth the structural complexity measure (see Figure 4 & 5). This reduced the sharp drops in the structural complexity measure caused by large amplitude artefacts as mentioned in Section 4. A range of structural complexity values that characterized the non-seizure period was then calculated such that 5% of structural complexity values were outside this range.

To reduce false detection rate $P_F$, a requirement was included in which a minimum length of twenty seconds of seizure structural complexity levels was needed for a seizure to be registered. That is, structural complexity levels that indicated seizure had to be present in five or more consecutive epochs in at least one channel before the epochs would be officially classed as seizure. In the analysis of five newborns, this resulted in an average true seizure detection rate $P_T = 93.5\%$ with false alarms at $P_F = 4.5\%$.

## 6. CONCLUSION

In this paper a new signal measure, namely structural complexity, which relies specifically on the dictionary being used by MP, has been proposed. It has been shown that the structural complexity measure can be used to indicate a change in signal structure. Detecting a change in newborn EEG signal structure as it changes from the non-seizure state to seizure state has been shown to be an application of this measure. An automatic seizure detection algorithm has been proposed incorporating the structural complexity measure. The detection algorithm resulted in a true seizure detection rate of 93.5% in conjunction with a false alarm rate of 4.5%.

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