AUTOMATED BURST DETECTION IN NEONATAL EEG

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Keywords: Electroencephalogram (EEG), Neonatal Intensive care Unit (NICU), EEG Burst Suppression, Amplitude integrated EEG (aEEG).

Abstract: Presence of burst suppression pattern in neonate EEG is a sign of epilepsy. Detection of burst patterns is normally done by visual inspection of recorded raw EEG or amplitude integrated EEG signal. Existing automatic burst detection approaches consist of either supervised learning mechanism or static energy threshold based comparison. Both approaches can produce inconsistent results for babies with different ages (for example, a neonate EEG and a six month old baby EEG). That is because, EEG signal amplitude or energy increases according to baby's age. Training based classifiers or static thresholds cannot adapt with this amplitude variation. Here we propose an automatic burst detection method, which first computes signal parameters such as energy, variance and power spectral density. From generated signal data, so called low level amplitude or energy output is used as a ground reference for indication of signal suppression level. Burst is identified according to high deviation of parameter values from those in suppression pattern. It does not need any static threshold based comparison. Results show that our algorithm exhibits greater sensitivity and equal specificity than existing methods. Due to adaptive thresholding for burst detection, our method is applicable for analyzing EEG signals of babies with different ages.

1 INTRODUCTION

Electroencephalogram (EEG) monitors cerebral electrical activities through electrodes placed on scalp and provides a sensitive real time graphical representation of brain function. Especially for neonates, neurophysiological disorders and seizures are mostly diagnosed by visual inspection of EEG signals. Reason behind that is, unlike the seizure cases in adults or matured children, neonates commonly do not exhibit clinical sign and symptoms (Connell et. al., 1989) for seizures. Thus visual inspection of EEG for monitoring seizures is a standard of care for most neonatal intensive care units (NICUs) around the world (Rennie, 2008; Sanei, 2007).

Burst suppression pattern is one of the typical abnormal EEG patterns which are seen in neonatal seizures. It is a pattern of high amplitude activity interrupted by relatively low amplitude activity typically less than twenty micro volts peak-to-peak. High amplitude activity is termed as burst, whereas low amplitude activity is termed as suppression. Together, the burst-suppression patterns usually have duration of a few seconds. They occur in an unpredictable, irregular fashion. Repeated occurrence of burst-suppression patterns produces a burst-suppression cycle or event, which can be used to predict epilepsy. Burst portions contain physiological burst (normal) and pathological burst or seizures (if present). Generally, visual inspection of raw EEG signal is employed to detect burst-suppression pattern. This visual detection is very much subjective to the respective viewer (Löfhede, 2008; Löfhede, 2010; Wang, 2007).

Burst detection using amplitude integrated EEG (aEEG) (Hellström-Westas L, 2008; Maynard et. al., 1969, 1971) is quite common now. Here, input raw EEG signal is first band pass filtered in the frequency range 2-15 Hz to attenuate electrical activities outside this range. Filtered EEG is then rectified (i.e. negative voltages are converted to positive values) and peak to peak voltages are measured. Finally smoothing and semi-logarithmic scale based compression is applied. It is very helpful in detecting long term EEG trends (of several hours, for example). Prolonged burst patterns can be

Bhattacharyya S., Mukhopadhyay J., Majumdar A., Majumdar B., Singh A. and Saha C..
AUTOMATED BURST DETECTION IN NEONATAL EEG.
DOI: 10.5220/0003123900150021
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2011), pages 15-21
ISBN: 978-989-8425-35-5

identified through visual inspection of single channel or multiple channel aEEG patterns. But, short term bursts cannot be easily identified from the compressed logarithmic scale display of aEEG patterns (Hellström-Westas L, 2008). Thus, considering huge amount of recorded data, it is necessary to develop mechanisms for automatic detection of burst suppression patterns, without any need of visual inspection.

Section 2 lists earlier works on the proposed topic. Section 3 describes our approach. Finally in section 4, we show that our proposed approach has a consistent high performance in detecting burst patterns for babies of any age.

2 RELATED WORKS

There are many burst detection algorithms which are classified based on whether they use any training data for supervised learning and classification, or whether they use static threshold based burst pattern detection.

Automated burst detection algorithm using non linear energy operator (NLEO), applied upon EEG band and artefact band signal (Palmu, 2010; Särkelä, 2002) falls in the second category. In this algorithm, EEG signal is first divided in two frequency bands: 1) EEG band (*0.1-8* Hz), 2) Artefact band (*47-49* Hz). For each sample *i*, if we say that *x(i)* is the value of corresponding band filtered EEG at that sample, then NLEO output for that sample is written as:

$$NLEO(x(i)) = x(i)\,x(i-3) - x(i-1)\,x(i-2) \qquad (1)$$

For each sample *i*, difference of NLEO outputs between EEG band and artefact band signals is evaluated as follows.

$$DIFF(x(i)) = NLEO\_EEG\_band(x(i)) - NLEO\_artefact\_band(x(i)) \qquad (2)$$

If this difference is persistently greater than certain predefined burst threshold value for at least minimum burst duration (which is set as *1* second), then the algorithm notifies occurrence of a burst pattern. Similarly, if this difference stays below a fixed suppression threshold for a certain period of time then it indicates the occurrence of a suppression pattern.

This fixed threshold based burst pattern detection method, however, leads to two kinds of drawback:

1) Recorded EEG signal amplitudes or energy values increase along with baby's age. Thus, static threshold value based decision is not suitable for burst detection over babies of different ages.
2) Ranges of EEG amplitudes or energy values vary on different recording channels. For example, involvement of occipital channel (O1 or O2) results in generation of higher EEG amplitude than EEGs from frontal channel (FP1 or FP2). Thus a fixed threshold cannot properly detect burst in all channels.

Figure 1 shows false burst detection for one EEG of six month old baby, throughout the channels P4-O2 and P3-O1, for the NLEO based algorithm as discussed above. The display has sensitivity *15 µv/mm* and time base *15 mm/sec*. Due to static threshold based calculations, high amplitude recordings are misclassified as bursts. On the other hand, bursts in frontal channels FP1 or F8 can not be detected because of their relatively low amplitude.

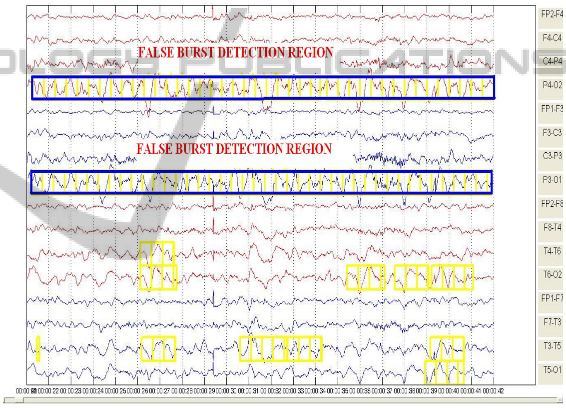

Figure 1: False burst detection (marked in blue rectangles) for NLEO based algorithm for a 6 month old baby, for channels P4-O2 and P3-O1. Here, high amplitude recordings throughout are misclassified as bursts.

In other words, for the NLEO based algorithm, high amplitude recordings (compared to the predefined static burst detection threshold) are always detected as bursts. Similarly, bursts in relatively low amplitude recordings may not be detected.

Another algorithm based on computation of moving instantaneous amplitude and comparison with threshold (Wang, 2007) has the provision of dynamically setting the amplitude threshold. But it is dependent upon visual perception, rather than individual channel data based adaptation. So it also does not generalize burst suppression detection for babies.

Algorithms which use training data based supervision extract several features like spectral edge frequency, *3* Hz power, median, variance, Shannon entropy (Löfhede, 2008, 2010; Greene, 2008) etc. Training data is obtained by feature values at burst instances which are manually marked by experts. But this training based algorithm which uses feature values during burst duration, is also not free from the problem of false burst detection or non-detection during high or low amplitude EEG signals.

A general burst suppression pattern detector should consider transition of feature values from burst to suppression or background EEG or vice versa. This analysis should be adaptive as per individual channel data, so as to avoid misclassification for wide variety of samples. Our approach adapts burst or suppression thresholds according to channel data. Using these adaptive thresholds, burst patterns are detected. It leads to generalized and high performance burst pattern detection despite the variation of baby's age or channel data.

3 PROPOSED METHOD

3.1 Dataset

We perform the study over eight full term infants having epileptic data and clear burst suppression pattern. The data set is obtained from Department of Neonatology, SSKM hospital, Kolkata, India. During data recording, bipolar longitudinal montage with sixteen electrodes is used, according to international *10-20* standard (Rennie, 2008), at positions FP1, FP2, F3, F4, P3, P4, O1, O2, C3, C4, T3, T4, F7, F8. Voltage difference of two electrodes is used as the input data, for example P4-O2 or C3-P3. Each data has duration of *20* to *30* minutes. The data covers babies of age from *6* days to *8* months. Thus detecting proper burst patterns in this dataset confirms generalized utility of our approach.

At least ten multi channel burst patterns are present in each input data. Burst patterns are manually marked by doctors. They also identify and mark the artefacts to separate them from burst patterns. In our algorithm, we check for only correct burst pattern detection; detection of artefacts and automatic separation of them from burst patterns is not exercised.

3.2 Feature Extraction

The available data is digitized at a sampling rate of *256* Hz and band pass filtered between *0.5* to *20* Hz. The band pass filter has its high pass component of a 1^{st} order Butterworth filter and low pass component of a 6^{th} order elliptic filter. For the feature extraction purpose, a sliding window of *1* second time resolution and *0.5* second displacement is applied. That is, features are extracted for second intervals *1-2, 1.5-2.5, 2-3* and so on. Following features are extracted for each time interval of *1* second duration:

1) Mean non linear energy (Greene, 2008)
2) Variance (Löfhede, 2008),
3) Power spectral density (Welch, 1967),
4) Total sum of absolute values of amplitudes.

If $x(i)$ is the value of filtered EEG for sample i residing in the window interval then mean non linear energy (MNLE) for that window interval is given by equation (3). For a burst pattern, mean non linear energy value goes significantly higher from that of a background or suppression EEG pattern.

$$\text{MNLE} = \sum (x^2(i) - x(i-1)\, x(i+1)) \quad \text{for all sample } i \text{ lying within window interval} \tag{3}$$

Similarly, variance (VAR), given in the equation (4), has a significantly higher value in case of a burst pattern occurrence as compared to its value during background or suppression EEG pattern.

$$\text{VAR} = (1/(n-1)) \sum (x(i) - \mu)^2 \quad \text{for all sample } i \text{ lying within window; } \mu \text{ is sample mean} \tag{4}$$

Power spectral density (PSD) shows the distribution of signal power with respect to frequency. Total PSD value over bandwidth of signal under one window interval is significantly higher during burst pattern occurrence, as compared to its value in background or suppression EEG.

Sum of absolute voltage values in signal under one window interval has high value during burst and comparatively much lower values during background or suppression EEG.

All the feature extraction and subsequent implementation is done in MATLAB version 7.8.0.

3.3 Burst Detection Algorithm

Generally, for visual detection of a burst pattern, necessary sensitivity adjustments in display interface are made in order to first make the so called general amplitude output as a ground reference. Then bursts are detected based on high signal fluctuations from the average outcome. This principle is applied in our burst detection algorithm.

In burst intervals, extracted feature values deviate highly from their normal or average values (i.e. values in background EEG patterns). To detect burst portions, we need to determine two things:

1) Meaning of average or background EEG pattern and how it is represented by features mentioned in section 3.2.
2) Benchmark of deviation of feature values in burst portions as compared with average or background EEG pattern.

We model average or background EEG pattern by implementing separate circular queues for different features like mean non linear energy, variance and power spectral density. Each queue stores respective feature values of last five seconds corresponding to suppression or close to suppression intervals. Thus effectively it stores ten feature values because overlapping window is of *0.5* second displacement and *1* second resolution. Initially each queue contains median value of respective feature data generated from total signal.

Current EEG portion under analysis is marked by sliding window. If current EEG portion has feature value less than or close to the mean value of feature data currently stored in the queue, then we decide that current EEG portion is from background or average EEG pattern. In that case, current feature data is stored in respective feature queue. Queue update for each feature is thus independent of other feature queue updates. Using a circular queue enables replacement of least recent data with current one, provided the queue is already full.

To determine whether current EEG portion is a burst, we compare extracted feature values with respect to mean feature values of respective queue. Formally, we define val_{nle}, val_{var}, val_{psd}, and val_{amp} as values of mean non linear energy, variance, power spectral density and sum of absolute voltages for current EEG portion. These values change as queue elements are updated with latest background EEG data. Similarly, $mean_{nle}$, $mean_{var}$ and $mean_{psd}$ are defined as mean values of queues storing non linear energy, variance and power spectral density respectively.

If current EEG portion generated feature values (val_{nle}, val_{var} and val_{psd}) are greater than the mean values of feature queues ($mean_{nle}$, $mean_{var}$ and $mean_{psd}$ respectively) by some multiples, then we label current portion as possible burst. But, as we model the EEG burst with respect to current channel background EEG data, it may happen that current possible burst portion has very low amplitude, thus not visually identifiable as burst. This case can happen when background EEG has very low activity for some time. So we compare the sum of absolute voltages for current EEG portion (val_{amp}) with respect to a predefined threshold. If the voltage sum is greater than the threshold then current region is labeled as a burst. The algorithmic steps are shown in figure 2.

Input:
Feature values of current EEG window.
Output:
Current EEG portion is burst or not (Boolean decision). If true, we mark the burst start and end times.
Variables:
z1, z2, z3 are integers. *th* is voltage threshold.
z1 = z2 = z3 = 5 (experimentally set)
th = 15000 (experimentally set)

Algorithmic Steps:
1) If (*valnle > z1 × meannle*) **and** (*valamp > th*)
If (*valvar > z2 × meanvar*) **or** (*valpsd > z3 × meanpsd*)
Mark start of current time interval as burst start time.

2) If *conditions in step 1 are **not** met* **and if** *there is an ongoing burst interval* **then**
Mark ongoing burst end time equal to midpoint of current time interval.

3) If *valnle* is less than or very close to *meannle* **then** add it in the circular queue for non linear energy values. Similarly queues of variance and power spectral density are updated if *valvar* is less than or close to *meanvar* and *valpsd* is less than or close to *meanpsd* respectively.

Figure 2: Our proposed burst detection algorithm.

If, for time interval between *x* second to *(x+1)* second, extracted features confirm start of a burst, then burst start time is set as *x* second (according to step 1). Now, if for the next analyzed time interval (that is, between *(x+0.5)* second to *(x+1.5)* second), features confirm end of the burst (according to step 2), then burst end time is marked as the midpoint of current time interval; that is *(x+1)* second. So, in effect, time interval *x* to *(x+1)* is marked as a burst interval. Minimum burst duration is thus set to *1* second.

Finally, we mark the burst intervals generated from above algorithm in a custom signal display interface to visually check and compare with existing approaches.

4 EXPERIMENTAL RESULTS

We executed our approach in the dataset mentioned in section 3.1. We have also implemented NLEO based algorithm (Palmu, 2010; Särkelä, 2002). We perform both visual and statistical comparisons between outcomes of these two algorithms. Input data set was examined by doctors and burst patterns were marked by them. We evaluate and validate performances of both algorithms with respect to marked burst patterns.

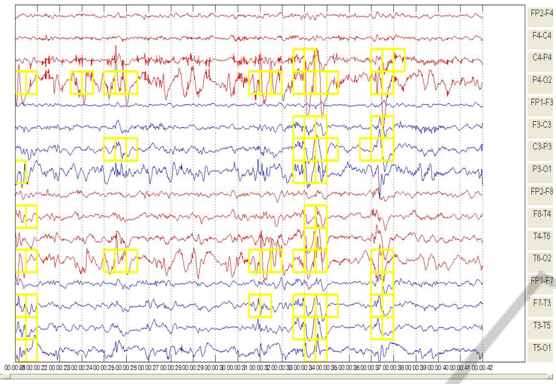

Figure 3: Correct burst detection case (marked in yellow) for channels P4-O2 and P3-O1 in our algorithm corresponding to figure 1.

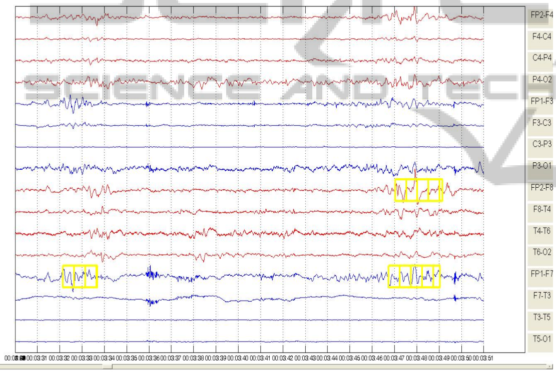

Figure 4: Burst detection in NLEO based algorithm for a 10 days old baby; it can't detect bursts in FP2-F4 and FP1-F3 channels (channel no 1 and 5 respectively from top in display).

In figure 3, we show that our algorithm performs correct burst detection in channels P4-O2 and P3-O1, as corresponding to the false burst detection region cases for NLEO based algorithm (which was shown in figure 1). Rather than detecting whole channel data as burst, due to static amplitude thresholds, it uses the fact that, throughout for the channels P4-O2 and P3-O1, background EEG amplitude is quite high. So, corresponding burst patterns are of quite high amplitude than other channels.

Figures 4 and 5 show that our result is comparable with the NLEO based algorithm even in neonate EEG recording cases. For a *10* days old baby, our algorithm detects correct burst cases in multiple channels as compared to old NLEO based (Palmu, 2010; Särkelä, 2002) approach, which cannot detect burst in channel FP2-F4 or FP1-F3.

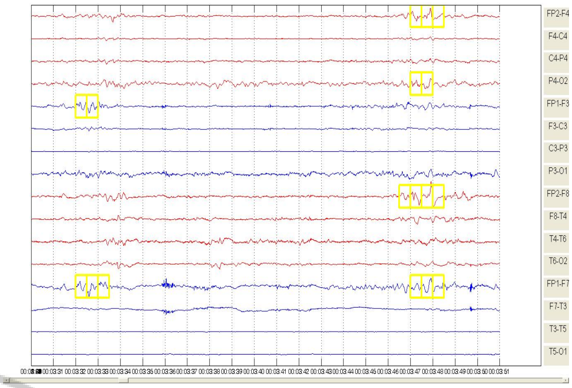

Figure 5: Burst detection in our algorithm as corresponding to the case in Figure 4; it detects bursts in FP2-F4 and FP1-F3 channels.

For very acute burst suppression pattern detection also, our algorithm does better than existing approach. Figures 6 and 7 show EEG of a *32* days old neonate. NLEO based algorithm cannot detect burst in any channel, whereas our algorithm detects burst for most of the channels.

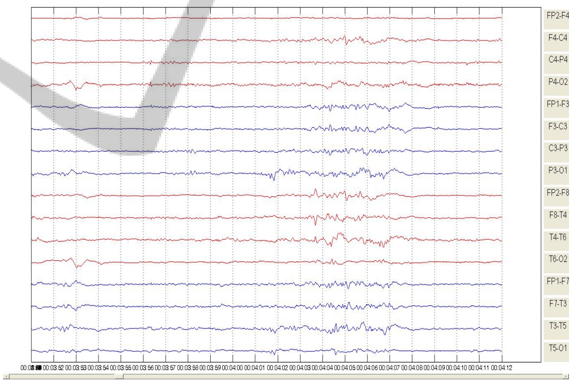

Figure 6: No burst detection in NLEO based algorithm for a 32 days old neonate.

For statistical measure based performance evaluation, we calculated sample sensitivity and specificity. They are defined in equations (5) and (6) respectively.

$$\text{Sensitivity}\,(\%) = \frac{(\text{True Positive} * 100)}{(\text{True Positive} + \text{False Negative})} \qquad (5)$$

$$\text{Specificity}\,(\%) = \frac{(\text{True Negative} * 100)}{(\text{True Negative} + \text{False Positive})} \qquad (6)$$

True positive means that a burst is detected by both visual and automatic detection.

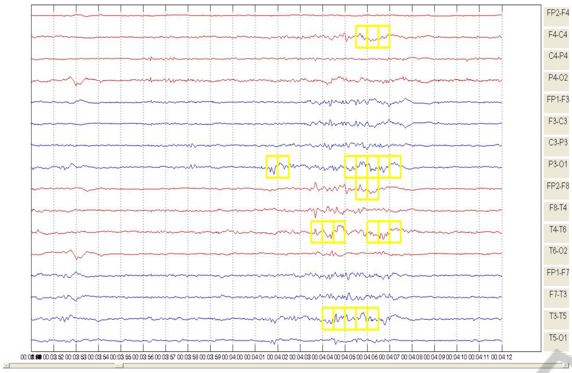

Figure 7: Burst detection (marked in yellow) for our algorithm corresponding to the case of figure 6.

True negative means that absence of burst is detected by both visual and automatic detection.

False positive result occurs when automatic method indicates a burst whereas visual detection cannot find anything.

Lastly false negative case occurs when automatic detection method indicates no burst whereas visually a burst is marked.

The computation includes outcomes for all *16* channels. That is, for a particular multi-channel burst, if burst for *4* channels are marked originally, and our algorithm detects only *3* of them then sensitivity is calculated as *75%*.

We show tabular data of sensitivity for both old NLEO based approach and our algorithm, executed upon previously mentioned dataset. At first, multi channel burst patterns for all the channels are marked by doctors. We select the data files such that there exists at least *10* visually identifiable multi channel burst patterns. Then both algorithms are executed to detect the percentage of bursts that are correctly identified, for all the marked channels. It is the required sensitivity value.

It is to be mentioned that, for NLEO algorithm, maintaining same static burst detection threshold for all input data gives poor result. So we calculated separate optimum thresholds, specific to each of the test data. These thresholds are then applied with NLEO algorithm. Thresholds are set in such a fashion that false positive cases are almost eliminated. In our algorithm also, we found almost zero false positive case for each of the test data. Thus both algorithm exhibits almost same specificity value (close to *100%*) for all the test data. We compare relative sensitivity values for these two algorithms and show comparative results in Table 1.

We can see that in all cases except result 4, sensitivity is higher in our algorithm. Also, NLEO based outcome is highly dependent on choosing correct burst detection threshold (which we did set manually by observation for each experiment). On the other hand, our algorithm's dynamic adaptation of thresholds based on channel data gives it slight edge.

Table 1: Sensitivity comparison for 2 algorithms using dataset of neonate and baby EEG

Sl No	Age (D= days, M= month)	No of multi-channel burst patterns seen	Sensitivity with old NLEO algorithm (%)	Sensitivity with our algorithm (%)
1	6 D	12	94.18	95.35
2	10 D	10	67.44	88.37
3	16 D	25	89.36	95.74
4	39 D	24	95.16	93.0
5	3M	21	79.5	98.7
6	6M	30	86.5	94.6
7	6M	35	84.06	97.15
8	8M	39	92	97

If burst detection threshold is set quite low in NLEO algorithm, then for high amplitude signals, it shows continuous burst, increasing false positive rate (similar to the case shown in figure 1). Our algorithm is free from any such false positive case detection.

5 CONCLUSIONS

We have described a simple dynamic threshold based automatic burst detection algorithm. It can be used in analyzing EEG bursts for neonates and also for matured babies. So far, EEG data of babies up to eight months are experimented. It can be further tested and upgraded to include automated burst detection for children of higher age, and possibly for adult EEG also. Bursts of minimum one second duration are detected in our algorithm. It can be augmented to include sudden spikes of length less than one second, for any further research.

ACKNOWLEDGEMENTS

This project is funded by Ministry of Communications and Information Technology, Government of India; under project grant number 1(4)/2009-ME&TMD. We are thankful to our colleagues and to the doctors of neonatology department, SSKM Hospital for helping us in data collection, marking, and analysis.

REFERENCES

Connell, J. & Oozeer, R. & De Vries, L. S. & Dubowitz, L. M. S. & Dubowitz, V. (1989). "Continuous EEG monitoring of neonatal seizures: diagnostic and prognostic considerations", in *Archives of Disease in Childhood, 1989, 64, pp. 452-458.*

Greene, B. R. & Faul, S. & Marnane, W. P. & Lightbody, G. & Korotchikova, I. & Boylan, G. B. (2008). A comparison of quantitative EEG features for neonatal seizure detection. in *J Clin Neurophysiol 2008*, doi:10.1016/j.clinph.2008.02.001

Hellström-Westas, L. & De Vries, L. S. & Rosén, I. (2008). *Atlas of Amplitude Integrated EEGs in the newborn*, informa healthcare. UK, 2nd edition, ISBN-13: 978 1 84184 649 1

Löfhede, J. & Löfgren, N. & Thordstein, M. & Flisberg, A. & Kjellmer, I. & Lindecrantz, K. (2008). Classification of burst and suppression in the neonatal electroencephalogram. in *J Neural Eng 2008;5:402–10.*

Löfhede, J. & Thordstein, M. & Löfgren, N. & Flisberg, A. & Rosa-Zurera, M. & Kjellmer, I. & Lindecrantz, K. (2010). Automatic classification of background EEG activity in healthy and sick neonates. in *J. Neural Eng. 7 (2010) 016007*

Maynard, D. E. & Prior, P. F. & Scott, D. F. (1969), Device for continuous monitoring of cerebral activity in resuscitated patients. in *Br Med J 1969;4:545-6.*

Palmu, K. et al. (2010) Detection of 'EEG bursts' in the early preterm EEG: Visual vs. automated detection. in *J Clin Neurophysiol 2010*, doi:10.1016/j.clinph .2010.02.010

Prior, P. F. & Maynard, D. E. & Sheaff, P. et al. (1971). Monitoring cerebral function: Clinical experience with new device of continuous recording of electrical activity of brain. in *Br Med J 1971;2:736-8.*

Rennie, J. M. & Hagmann, C. F. & Robertson, N. J. (2008). *Neonatal Cerebral Investigation*, Cambridge University Press. New York, 1st edition, ISBN-13 978-0-511-41368-1

Sanei, S. & Chambers, J. A. (2007). *EEG Signal Processing*, John Wiley & Sons. England, ISBN-13 978-0-470-02581-9

Särkelä, M. & Mustola, S. & Seppänen, T. & Koskinen, M. & Lepola, P. & Suominen, K. & Juvonen, T. & Tolvanen-Laakso, H. & Jäntti, V. (2002). Automatic Analysis and Monitoring of Burst Suppression in Anesthesia. in *J Clin Monit Comput 2002;17:125–34.*

Wang, Y. & Agarwal, R. (2007). Automatic Detection of Burst Suppression. in *IEEE EMBS INTL Conf Aug 2007*.

Welch, P. D. (1967). The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms. in *IEEE Transactions on Audio Electroacoustics, Volume AU-15 (1967), pages 70–73.*