IMPROVEMENT AND VALIDATION OF AN AUTOMATED NEONATAL SEIZURE DETECTOR

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Abstract: We present the improvements made to and subsequent validation of an automated approach to detect neonatal seizures. The evaluation of the algorithm has been performed on a new and extensive data set of neonatal EEGs. Previously, we have classified neonatal seizures visually into two types: the spike train and oscillatory type of seizures and developed two separate algorithms that run in parallel for their automated detection. The first algorithm analyzes the correlation between high-energetic segments of the EEG, whereas the second one detects increases in low-frequency activity (<8 Hz) and then uses an autocorrelation. An improved version of our automated system (called 'NeoGuard') uses more informative features for classification and optimized parameters for thresholding. The validation was performed on 756 hours of 'unseen' continuous EEG monitoring data from 24 neonates with encephalopathy and recorded seizures. The seizure detection system showed a median sensitivity of 86.9 % per patient, positive predictive value (PPV) of 89.5 % and false positive rate of 0.28 per hour. The modified algorithm has a high sensitivity combined with a good PPV whereas false positive rate is much lower compared to the previous version of the algorithm.

1 INTRODUCTION

Neonatal seizures occur in 1 to 3.5/1000 births and they represent a distinctive indicator of abnormality in the central nervous system – CNS (Volpe, 2001). The etiologies are varied, with the majority being caused by biochemical imbalances within the CNS, hypoxic ischemic encephalopathy, intracranial haemorrhages and infection, and developmental (structural) defects. Neonatal seizures are associated with major dysfunction of the CNS and result in significant sequelae (Holmes, 1998; Miller, 2002). Therefore, there is a high need for early detection of the seizures. Seizures detected in the early stages of life can be treated with anticonvulsant drugs and in that way, hopefully, further damage to the brain can be limited. In clinical practice, detection of the seizures is accomplished by a combination of clinical observation and visual assessment of the EEG. However, clinical signs need not always accompany neonatal seizures. They can manifest as subtle (Connell, 1989; Malone, 2009) or subclinical seizures, being only detected by EEG monitoring.

Many algorithms for detection of neonatal seizures have been published. The best known methods are based on computing a running autocorrelation function (Liu, 1992), rhythmic discharges detection (Gotman, 1994), modelling and complexity analysis (Celka, 2002). Other approaches have employed wavelets, frequency content, entropy, etc., for feature extraction. These features were then applied for supervised learning and training of classifiers (Greene, 2007; Zarjam, 2003; Aarabi, 2006).

At the moment, however, there is no neonatal seizure detection algorithm which is widely accepted in clinical practice. The design of a reliable seizure detection system is a challenging task as neonatal EEG during seizures has as extremely complex and variable morphology. Moreover, great difference among the seizure patterns can be present even

within the same patient (Lombroso, 1996; Shewmon, 1990).

We have previously published (Deburchgraeve, 2008) an algorithm for automated neonatal seizure detection. It is designed with an approach which tries to mimic the decisions made by the clinical neurophysiologist while visually examining EEG. In order to detect a neonatal seizure, the human observer searches for a pattern which shows a visible change relative to the background EEG. An additional main characteristic of all seizures is repetitiveness, as there is always a recurrent pattern which describes the seizure. Both features were employed for the algorithm design.

Due to the nature of the problem, the neonatal seizure detection system has to be very reliable and robust. Therefore, constant improvement, validation, and optimization of the algorithm are needed. The modified version of our detection system, called NeoGuard, was tested on a new, large set of unseen EEG data. We present here the results of the validation of our detection system.

2 METHODS

2.1 EEG data set

All EEG data were recorded at the Sophia Children's Hospital – part of Erasmus MC, the University Medical Center in Rotterdam, the Netherlands. The data base is formed from 24 consecutive newborns with presumed perinatal asphyxia who underwent video–EEG monitoring for at least 24 hours and had recorded seizures. The recordings mostly started within 24 hours of birth. Digital video–EEG with polygraphy, was registered continuously for 1-3 days using a Nervus™ monitor (Taugagreining hf, Reykjavik, Iceland). Seventeen scalp electrodes were placed according to the full 10-20 International System (Cherian, 2009). The sampling frequency was 256 Hz. It is important to stress that we have used a completely new data set for this study, with no overlap with the one that has been described previously (Deburchgraeve, 2008). All EEG data was reviewed by a clinical neurophysiologist and the seizures were visually scored for their onset, amplitude, frequency, duration, rhythmicity, location and spread. We defined as 'definite seizures' electrographic discharges that showed a clear variation from background activity, displaying a repetitive pattern of oscillations or sharp waves or a mixture of both, lasting ≥10 seconds, with evolution in amplitude and frequency over time. We classified discharges as 'dubious seizures' when a) runs of sharp waves /oscillations or a mixture of both occurred arrhythmically (with marked variability in the interval and morphology between individual complexes for the major part of its duration) or b) rhythmic discharges of shorter (<10 sec) duration or periodically occurring sharp waves or mixed patterns. It was difficult to identify the onset and offset of such discharges and sometimes difficult to clearly identify them as a variation from ongoing EEG background. We chose to group them under 'seizures' as they were seen to recur paroxysmally during the monitoring.

2.2 Updates of the automated seizure detection algorithms

During the visual analysis of the neonatal seizures we have identified two major morphological types. The first one represents the spike train seizures (Fig. 1A), whereas the second one represents the oscillatory seizures (Fig. 1B). We were able to classify almost all neonatal seizures as one of the two types or as their combination (Fig. 1C).

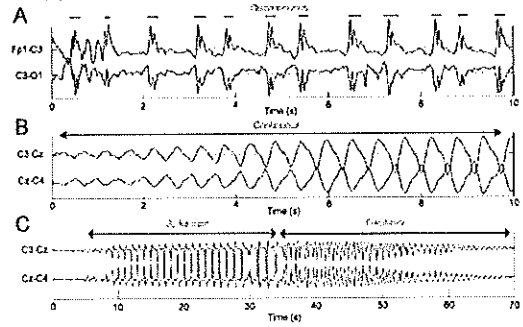

Figure 1: A. Spike train type seizure, B. Oscillatory type seizure, C. Combination of both morphologies.

The most prominent difference between the two seizure types is that the oscillatory type is continuous in time, whereas the spike train type consists of distinct, isolated spikes. Additionally, the oscillatory type is characterized by low frequency content and spikes represent a highly dynamic signal. Therefore, two separate algorithms were developed and different stages are discussed in detail in our previous work (Deburchgraeve, 2008). The basic idea to detect a spike train seizure is to segment isolated spikes and to compare their morphology. We will regard spike train as a seizure if the overall similarity between spikes is sufficiently

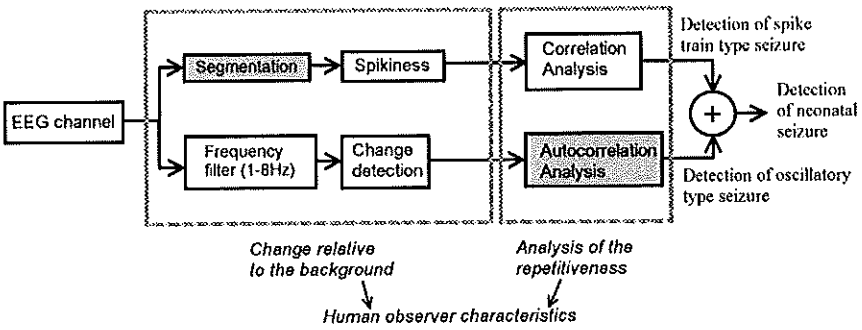

Figure 2: Schematic overview of the complete neonatal seizure detection algorithm.

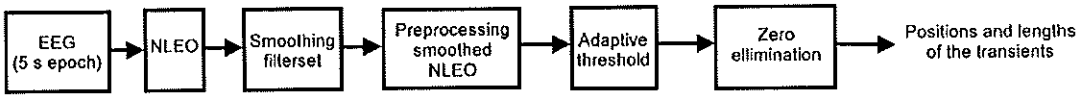

Figure 3: Schematic overview of segmentation steps of the spike train detection

high. On the other hand, oscillatory seizures are continuous and have low frequency values. At first, we detect the oscillatory segments by filtering and monitoring the increase of the low frequency content (< 8 Hz). After that, we examine the presence of oscillatory seizures by analysis of the autocorrelation function of the corresponding signal segment. The updated stages of the detection algorithm are shaded in grey in Fig. 2. The most important improvement concerns a change in the segmentation strategy for the spike train type detection. As far as the detection of the oscillatory seizures is concerned, only the analysis of the autocorrelation function has been changed. Details on the other blocks can be found in the previous paper (Deburchgraeve , 2008).

2.2.1 Segmentation of the spike train signal

The segmentation of the EEG sharp transients is important for the reliability of the spike train detection algorithm. This segmentation is performed separately on each channel of EEG, on a window of 5 seconds duration. There is an overlap of 4 seconds between subsequent windows under analysis. Fig. 3 shows a schematic overview of the updated algorithm.

We use the non-linear energy operator (NLEO) again to detect the local presence of a high frequency activity. In its discrete form it is given by:

$$\psi_{kaiser}\left[x(n)\right] = x^2(n) - x(n-1)\cdot x(n+1) \qquad (1)$$

The key property of the NLEO can be derived if we apply it on the discrete sinusoidal signal (Li, 2007):

$$\begin{aligned} x(n) &= A\cos(\omega_0 n + \theta) \\ \psi_{kaiser}\left[x(n)\right] &\approx A^2\sin^2(\omega_0 n) \approx A^2\omega_0^2 \end{aligned} \qquad (2)$$

When applied to spike train type seizure EEG, the NLEO effectively amplifies the high-frequency spikes while, on the other hand, attenuates the background EEG. The NLEO calculates the local energy of the signal using only a few samples. However, the spikes of a neonatal spike train type seizure vary in duration and can be of 50 ms length up to 500 ms. In order to adjust the sensitivity of the NLEO to the duration of the spikes, its output needs to be smoothed. However, it is not possible to find a single smoothing filter length that is adequate for both short (50 ms) and long (500 ms) duration spikes. This problem is solved by using a smoothing filter bank with 6 Moving Average (MA) filters with filter lengths of 2, 4, 8, 16, 32, and 64 samples respectively. The output signal of one filter is the input of the filter with next increasing MA filter length. The output of the filter bank is the summation of the outputs of each filter. This generates a smooth signal in which short as well as long spikes can easily be discriminated. Fig. 4C displays the smoothing effect on a spike

train type seizure with spikes of >500 ms duration. The arrows in Fig. 4B and C indicate that short peaks in the NLEO output are conserved by the smoothing: only variations of the NLEO output on a large time scale are smoothed out. This is exactly the desired behaviour of the algorithm: to be sensitive to spikes of both short and long duration.

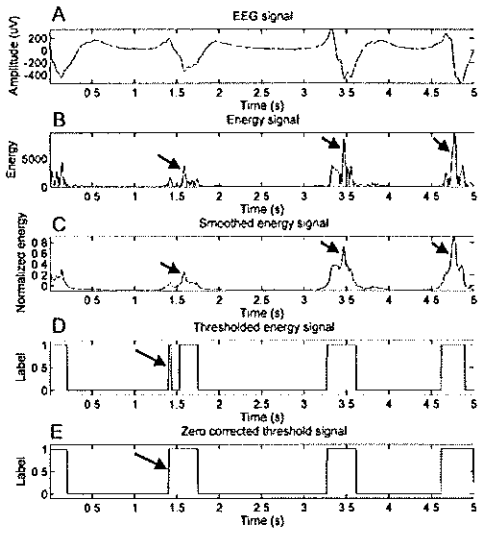

Figure 4: Illustration of the steps of the segmentation.

The goal of the next step is to find an adaptive threshold to discriminate between high and low energy values. After thresholding, the parts of the signal with high energy are transformed to isolated segments with a certain position and length. The threshold must be at a level that detects the transients in the EEG without segmenting small, insignificant variations in the energy signal. For this purpose, segmentation is performed for a set of thresholds between 0 and 1 with a step size of 0.02. For each threshold, the number of segments above the threshold is counted. The threshold that leads to the maximum number of segments is kept as the definite threshold. If several threshold levels lead to the same number of segments, the lowest one is taken.

2.2.2 Detection of the oscillatory seizure type – Autocorrelation analysis

As described previously (Deburchgraeve, 2008), algorithm for the oscillatory seizure type, has to detect segments with significant increase in the frequency band of 1–8 Hz. Autocorrelation function is computed for these segments and new features are extracted from it in this modified approach. In the updated version, three features are used to distinguish quasi-periodic segments:

- Regularity of the distances between the zero crossings (Fig. 5A), defined as 'errorZeros'.
- Regularity of the distances between the peaks (Fig. 5B), defined as 'errorPeaks'.
- Regularity of the normalized RMS values of the peaks which are delimited by the zero crossings (Fig. 5C), defined as 'errorRMS'.

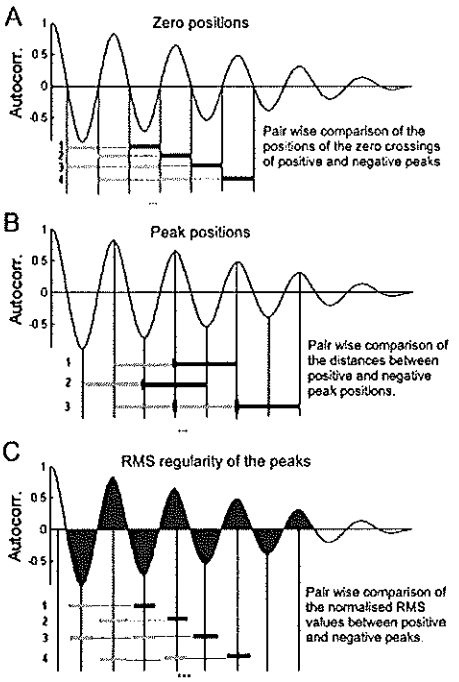

Figure 5: Illustration of the extracted features of the autocorrelation function

We have selected these features due to the fact that for an oscillatory signal, the phases of the autocorrelation function are regular. Hence, for oscillatory seizure activity, we may expect that the defined errors have relatively small values. Regularity was measured by means of a pair wise comparison of all the distances or RMS values involved. For this purpose, each difference between an element indicated with a dark grey bar compared with that indicated by a light grey bars is expressed as a percentage of their difference in length or area. (Fig. 5). For seizure detection, the thresholds on the features were defined as:

- median([errorZeros,errorPeaks]) < 7% and,
- median(errorRMS) < 10%

The comparisons for the zero crossings and the distances between the peaks can be grouped

together as both represent measures of distance. The comparisons for the RMS values are treated separately. All segments with properties below these thresholds are regarded as a part of an oscillatory seizure.

2.3 Validation of the improved algorithm

Different approaches for the quantification of the performance of neonatal seizure detection algorithms have been proposed by various researchers. Due to variations in patient population and methods of data collection, it is difficult to compare the results of the performance of various algorithms in a fair way. Therefore, we have decided to use several parameters to analyze the performance of the neonatal seizure detector.

We defined the sensitivity per patient (*SensPP*), as the percentage of the number of seizures marked by the clinical neurophysiologist that are detected:

$$SensPP = \left(SZ\,\mathrm{det}\,PP / SZtotPP\right)\cdot 100\% \qquad (3)$$

with *SZtotPP* representing the number of seizures marked by the neurophysiologist for each patient, and *SZdetPP* representing the number of automatically detected seizures for that patient. A seizure was considered detected when there was a temporal overlap between the marked seizure and the detection. The overall sensitivity (for all patients) was calculated using 2 methods. The first one, simply averages all sensitivities per patient (*SensT_PP*). The second method (*SensT*) measures the percentage of seizures detected of all seizures present in the complete 756 hours dataset. That is, *SensT_PP* represents the sensitivity at the patient level, whereas *SensT* represents sensitivity at the seizure level. The importance of the difference is that in *SensT_PP*, a patient with only a few seizures is considered to be equally important as a patient with many seizures. On the other hand, *SensT* considers all seizures equally important regardless of the patient they occurred in.

In addition, we used Positive Predictive Value (PPV). that is defined as the percentage of detected events that match seizures:

$$PPV = \left(EV\,SZ / EV\,tot\right)\cdot 100\% \qquad (4)$$

with *EV_tot* the total number of detected events and *EV_sz* the total number of detected seizures (i.e., events that overlapped with a seizure marked by the clinical neurophysiologist). Occasionally, a single seizure was detected several times by the algorithm. All such events were combined into a single *EV_sz* detection. In practical terms, *PPV* gives the probability that the detector has detected a true seizure for each detection. The duration of the event is not taken into account. *PPV* is event-based and, therefore, depends on the a priori likelihood of seizures ('prevalence') in the dataset. Hence this measure is difficult to compare between different data sets. Nevertheless, it is an interesting performance measure of the detector.

Last but not least, we have quantified a measure of the number of False Positive detections per hour (*FP/h*). This measure directly represents the practical usability of the algorithm, because each FP implies that somebody in the neonatal intensive care unit (NICU) will have to check the patient and the raw EEG recording unnecessarily.

3 RESULTS

During the analysis, we have examined 756 hours of EEG data. Median duration of EEG recording was 25 h (range 17 to 78) per patient. The algorithm gives an output of the number of events detected, the position in time where the event was detected and the duration of the detected events. A total of 2103 seizures were scored visually (median 67 per patient, range 7-236). Detailed results of the validation are presented in Table 1.

In four patients with severely abnormal EEG background activity and predominantly dubious seizures, the algorithm performed very poorly. As it was doubtful whether this recurring paroxysmal activity constituted genuine seizures, we excluded these patients. These were the patients 12, 13, 21, 23 in Table 1. Examples of dubious seizure patterns are presented in Fig. 6 and 7. In the remaining 20 patients, the algorithm showed a SensPP of 86.9%, PPV of 89.5% and Fp/h of 0.28/h (in total 643 hours of EEG data, 1263/1538 seizures detected, SensT 82.1%).

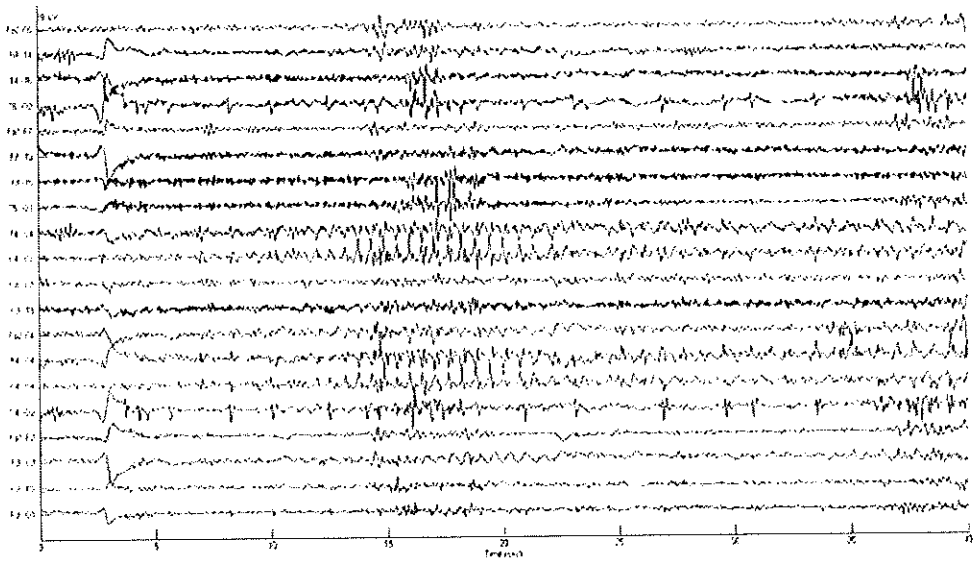

Figure 6: Dubious seizures characterized by brief rhythmic discharges and periodic sharp waves. Such seizures were variably detected by the algorithm.

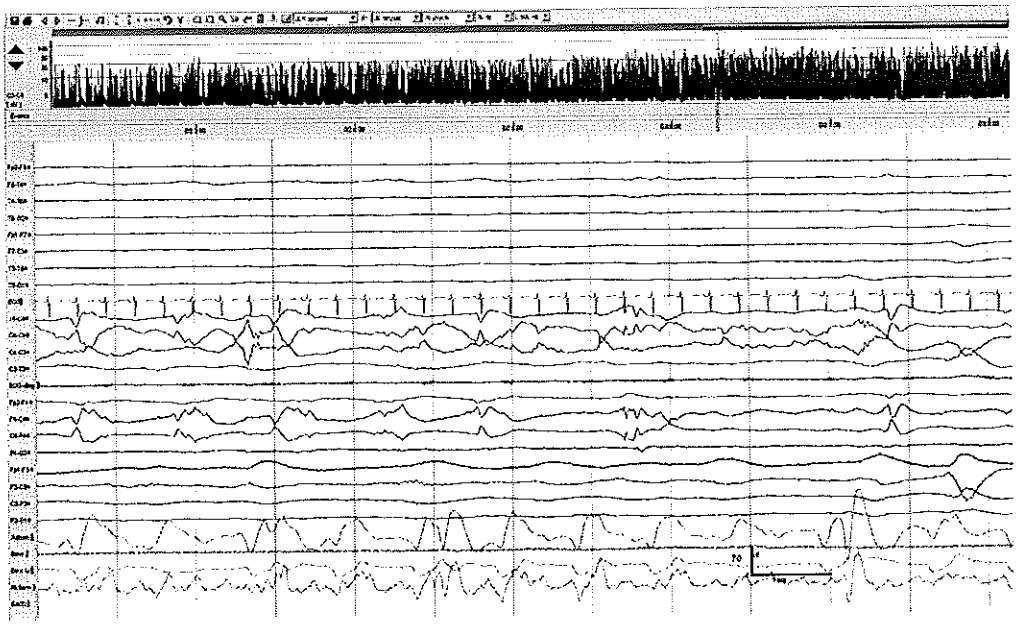

Figure 7: Dubious seizure over right central region characterized by a mixture of arrhythmic slow and sharp waves, not detected by the algorithm.

N_0	Sz det	Sens	Fp	PPV	Fp/h
1	52/53	98	21	84	0.88
2	10/18	56	1	92	0.04
3	28/48	58	19	60	0.42
4	30/34	88	34	47	2.00
5	56/63	89	0	100	0
6	12/13	92	4	75	0.17
7	104/109	95	0	100	0
8	8/8	100	0	100	0
9	93/98	95	0	100	0
10	6/7	86	6	50	0.26
11	110/112	98	6	95	0.29
12	0/210	0	45	0	0.09
13	1/70	1	8	11	0.33
14	47/50	94	3	94	0.13
15	30/72	42	7	81	0.17
16	18/33	55	15	55	0.65
17	95/113	84	1	99	0.04
18	169/200	97	10	94	0.42
19	14/44	32	12	54	0.41
20	10/27	37	69	13	3.45
21	12/156	7	0	100	0
22	170/200	85	10	94	0.42
23	9/129	7	80	10	3.2
24	201/236	85	31	87	0.47

Table 1: Seizure detection results.

4 DISCUSSION AND CONCLUSIONS

In this paper, we have presented an improved version of the previously designed neonatal seizure detector. The validation was performed on a new and large dataset, which has not been used previously during the optimization of the algorithms. These results confirm the suitability of the detection system for long-term EEG monitoring in a NICU setting, especially for detecting 'definite seizures', that are similar to the discharges defined by most of the published literature on neonatal seizures.

Seizures with very low amplitude and short duration were missed by the algorithm and this has been reported by other authors as well (Mitra, 2009). More specifically, automatic detection of arrhythmic seizures of low amplitude and predominantly oscillatory morphology was poor, whereas arrhythmic seizures with sharp wave morphology were well-detected. As the morphology of the neonatal EEG is extremely variable, it is difficult to develop a patient-independent algorithm. Neonatal seizure definition and classification is still a developing field, and the performance of an automated detector depends very much on the predetermined definition of such discharges.

The clinical significance of the low amplitude arrhythmic seizures occurring in neonates with persistent, severely abnormal EEG background activity (suggestive of severe underlying brain injury) is debatable, and it is unlikely that detection and treatment of such paroxysmal discharges improves clinical outcome. More research needs to be done to better understand the pathophysiology of neonatal seizures and the clinical significance of seizures in patients with varying severity of brain injury. This is a prerequisite for identifying the types of seizures whose treatment with antiepileptic drugs will improve clinical outcome. Refinement of automated seizure detection methods can then be done, targeted at this subgroup.

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