30th Annual International IEEE EMBS Conference
Vancouver, British Columbia, Canada, August 20-24, 2008

Automated single channel seizure detection in the neonate

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***Abstract*— Neonatal seizures are the most common neurological emergency in the neonatal period and are associated with poor long-term outcome. EEG is considered the gold standard for identification of all neonatal seizures, reducing the number of EEG electrodes required would reduce patient handling and allow faster acquisition of data. A method for automated neonatal seizure detection based on two carefully chosen cerebral scalp electrodes but trained using multi-channel EEG is presented. The algorithm was developed and tested using a multi-channel EEG dataset containing 411 seizures from 251.9 hours of EEG recorded from 17 full-term neonates. Automated seizure detection using a variety of bipolar channel derivations was investigated. Channel C3-C4 yielded correct detection of 90.77% of seizures with a false detection rate of 9.43%. This compares favourably with a multi-channel seizure detection method which detected 81.03% of seizures with a false detection rate of 3.82%.**

Index terms – EEG; neonatal seizure; seizure detection

I. INTRODUCTION

Seizures in the neonate require immediate medical attention and represent a distinctive sign of central nervous system dysfunction. There is increasing evidence that neonatal seizures have an adverse effect on neurodevelopmental outcome, and predispose to cognitive, behavioural, or epileptic complications in later life [1]. Neonatal seizures occur in 6% of low birth-weight infants and in approximately 2% of all newborns admitted to a neonatal intensive care unit (NICU) [2]. Seizures in this age-group are often subtle, difficult to diagnose and may be clinically silent, particularly after antiepileptic drug treatment, making diagnosis by clinical observation alone unreliable. A system that could automatically detect the presence of seizures in newborn babies would be a significant advance, facilitating timely medical intervention.

Multi-channel electroencephalography (EEG) is considered the gold standard for identification and diagnosis of all neonatal seizures. However special expertise is required to accurately apply a full set of electrodes and this expertise is not usually available on a 24 hour basis. Application of a full set of EEG electrodes increases the time before an EEG recording can begin and also the handling time for patients that are often weak and vulnerable. A seizure detection algorithm employing fewer electrodes would allow results to be obtained faster and could be used by less experienced electroencephalographers. Recent research has found that the use of a reduced number of electrodes [3] may be effective in the visual detection of neonatal seizures. Shellhaas and Clancy [4] found that 78% of neonatal seizures were present in a single central channel (C4-C3). In a separate study Shellhaas et al [5] found that interpretation of the amplitude integrated EEG (aEEG) derivation of C4-C3, was low even among those experienced with aEEG and this derivation was particularly insensitive to short, low amplitude seizures.

Much research has been carried out on automated neonatal seizure detection. A number of reported algorithms are defined for a single channel of EEG and declare a seizure if seizure is detected in one or more channels [6]. More recent papers have reported algorithms based on multiple channels of EEG [7-9]. Due to the inter-relation between EEG channels, and the fact that the location of a seizure onset is not known in advance, one would expect a multi-channel seizure detection algorithm to outperform one operating from a single EEG channel. Neonatal seizures are often focal and migratory in nature. A seizure is often not present across all EEG channels or on any given channel for the entirety of the seizure. Continuous multi-channel EEG does not usually contain per-channel labeling of seizures and for this reason may not be suitable for training a single channel seizure detection algorithm. Such an algorithm must be trained using only channels and segments within a seizure that are labeled as containing definite seizure activity as well as segments of non-seizure EEG.

This study compares the effectiveness of an algorithm which operates on a single bipolar EEG derivation, but is trained using multi-channel EEG. This algorithm is compared against a multi-channel algorithm and aims to show the usefulness of two carefully chosen cerebral scalp electrodes for the automated detection of seizures in the neonate.

II. METHOD

A. Data set

A dataset of 17 recordings from 17 full-term (GA: 39-42 weeks, BW: 1830g-4875g) neonates containing 411 seizure events, with mean seizure duration of 4.06 minutes from 251.9 hours of neonatal EEG was employed in this study (data characteristics are summarized in Table I). All recordings were made at the Unified Maternity Hospitals, Cork, Ireland. The records have a mean duration of 14.8 hours and were sampled at 256Hz. Each recording contained 7-11 channels of EEG and one ECG channel and all data was recorded using the Viasys NicOne video EEG system. Electrographic seizures were identified and annotated by a neonatal electroencephalographer (G.B.B.). Due to the focal

This work was supported by Science Foundation Ireland (SFI/05/PICA/1836).

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and often migrating nature of neonatal seizures the involvement of a specific EEG channel in each seizure was not recorded. However, each seizure was examined by the electroencephalographer to determine if a visible seizure manifestation could be seen on channel C3-C4.

TABLE I
DATA SET CHARACTERISTICS. LENGTH REFERS TO RECORD LENGTH (HOURS). SEIZURE DURATION IS THE MEAN SEIZURE DURATION (MINS). C3-C4 REFERS TO THE NUMBER OF SEIZURES VISIBLE ON CHANNEL C3-C4.

#	Length	Seizures	Seizure duration	C3-C4
1	18.23	17	1.41	6
2	24.74	3	4.63	3
3	24.24	148	2.28	148
4	19.45	6	3.65	6
5	24.00	48	5.78	48
6	5.69	41	1.13	41
7	24.04	6	0.92	6
8	24.53	17	5.33	17
9	3.47	11	9.15	11
10	10.06	25	5.23	24
11	15.97	13	1.17	8
12	12.61	3	2.85	3
13	12.13	25	3.95	25
14	6.52	1	2.73	1
15	12.00	4	0.87	4
16	7.63	31	10.07	31
17	6.64	12	7.88	12
Total	251.95	411		394
Mean	14.82		4.06	

B. *EEG Pre-processing*

The EEG for each channel was band-pass filtered in the range 0.1-34Hz using a 5th order Chebyshev IIR filter. The EEG was then processed in 8 second (2048 sample) non-overlapping epochs.

C. *Artifact rejection*

A variety of artifacts can occur in the neonatal EEG signal [9]. In this paper we have rejected three kinds of artifact, namely: 'movement' artifacts which are large signal spikes caused by movement of the patient and electrode leads, 'zero-signal' artifact caused by the amplifier being 'powered-off' in the course of a recording and electrocardiogram (ECG) artifacts, i.e. segments of EEG corrupted by ECG.

To identify the artifact sections of the EEG, a zero mean EEG signal was first calculated by subtracting the mean of the EEG from each sample and then processing this signal as follows:

- The standard deviation of the absolute value of the signal was calculated and any signal samples greater than 20 times the standard deviation were flagged as 'movement' artifact.
- Any 8 second epoch whose mean was 100 times smaller than the 5% trimmed mean of the signal was flagged as 'zero-signal artifact'.

To identify an ECG artifact on the EEG:

- Each 8 second EEG epoch for each EEG channel was correlated with the ECG corresponding to that epoch. Any EEG epoch in which the correlation was greater than 0.7 (where unity denotes perfect correlation) was flagged as containing ECG artifact.

The combined artifact measures were then associated with each 8 second epoch for each EEG channel. Any epoch deemed to contain more than 1% artifact was rejected by the algorithm.

D. *Feature Extraction*

A previous study by the authors determined an optimum set of features for neonatal seizure detection [10]. Based on these results, seven features were extracted from each 8 second EEG epoch for each EEG channel:

- Spectral entropy (H_S)
- Shannon entropy (H_{SH})
- Spectral edge frequency (SEF)
- Nonlinear energy (N)
- Line length (L)
- Wavelet energy
- RMS Amplitude (RMS Amp)

E. *Classifier Model*

A regularized discriminant (RD) based classifier model was employed in this study. An RD model can be derived from the linear discriminant classifier model, (based on the Mahalanobis distance). It is defined completely by a mean vector for each class, a covariance matrix for each class and the regularization parameters. A recent study by the authors found the optimum values for these parameters [11]. An RD model assumes normal class distributions and equal variance across classes. The class conditional mean vectors and covariance matrices were estimated entirely from the training data. Weighting of the class conditional mean vectors and covariance matrices by the duration of each record was implemented as discussed by Greene et al [12]. This ensures that patients with varying amounts of data do not unduly influence or bias the training of the classifier model.

F. *Classifier Training*

The performance of the algorithm as a generalized or patient-independent classifier was estimated using cross validation across all records. To detect seizure activity from a *single* bipolar channel of EEG, the classifier model must be trained using *multi-channel* EEG, containing a variety of seizures. Each of these EEG seizure training samples must contain only those channels determined by an expert in neonatal electroencephalography to contain electrographic seizure activity. For this reason conventionally labeled multi-channel EEG is not suitable for training, as seizure is not necessarily present on all channels, and expert labeling of seizures does not contain per-channel information. To overcome this problem, separate training and test sets were defined for each patient.

1) Test Set

The test set for each of the 17 patients contained the entire multi-channel EEG for each recording. All data for each recording was included in the analysis regardless of record length or quality. The seizure detection performance of a number of bipolar EEG channels in a single channel seizure detection system was examined. The following bipolar EEG channels (taken from the 10–20 system of electrode placement, modified for neonates) were used as the test set (depending on which bipolar channel was being investigated), to examine the single channel seizure detection performance for each patient:

- C4-C3
- C3-T3
- C4-T4
- F3-C3
- F4-C4
- Cz-C4
- Cz-C3
- C4-02
- C3-01

2) Training set

An 'ideal' training dataset was defined for each patient. This training set was a subset of the testing dataset and consisted of a number of artifact-free, multi-channel EEG seizure segments of approximately one minute duration for each patient. This allowed a training set containing feature vectors derived from multi-channel EEG to have the same dimensionality as feature vectors derived from single channel EEG. Only those channels, noted by the electroencephalographer to have clear electrographic seizure manifestation (referred to as 'involved' in the seizure) were labeled as seizure samples and included in the analysis. All EEG channels were included for any seizure labeled as generalized. 50 separate seizures were included (2-3 representative seizures per patient), each employing between one and nine channels. An equal number of non-seizure multi-channel EEG segments were also selected for each patient. Each non-seizure segment was considered by the electroencephalographer to be completely free of seizure.

3) Cross validation using testing and training sets

17 fold cross validation was used to obtain an unbiased estimate of the generalized classifier performance for the single channel algorithm. This involved training the classifier model using the training datasets for (z-1) of the z records and using the test set for the z^{th} record to test the classifier performance and then rotating through the z possible combinations of training and test sets. The mean of the results for all iterations is taken as a patient-independent performance estimate. This test provides a measure of the algorithms' ability to generalize from the training set and classify 'unseen' records.

G. Algorithm Performance Measures

A number of performance metrics based around 8 second EEG epochs were employed in this study. The classification accuracy (Acc) is defined as the percentage of epochs correctly classified by the system. The sensitivity (Sens) and specificity (Spec) are defined as the percentage of labelled seizure and non-seizure epochs correctly identified by the system. The good detection rate (GDR) is defined as the percentage of seizure events as labelled by an expert in neonatal EEG, correctly identified by the system. If a seizure was detected any time between the start and end of an expert labelled seizure, this is considered a 'good detection'. The false detection rate (FDR), is given as a measure the number of false detections incurred by the algorithm. It is defined as the percentage of non-seizure epochs incorrectly labelled as seizure epochs.

Area under the ROC curve (ROC area) is used as the main metric of algorithm performance as it provides a good overall measure of seizure/non-seizure class discrimination.

III. RESULTS

When examined by an expert in neonatal EEG, electrographic seizures were present on the C3-C4 channel in 394 of 411 seizures. Automated seizure detection using a variety of bipolar channel derivations including channel C3-C4 was investigated. Table II shows the classification performance of the bipolar EEG channels in the single channel seizure detection algorithm when compared to a previously reported multi-channel automated seizure detection algorithm [11], which was developed and tested on the same dataset as the present study. Channel C3-C4 gives the best seizure detection performance (ROC area 0.80) when compared to each of the bipolar EEG channels considered, yielding a similar GDR to the multi-channel algorithm but with a higher FDR. C4-Cz (ROC area: 0.76) and C3-Cz (ROC area: 0.74) yielded the next best single channel seizure detection performances. Fig.1 shows ROC curves for each of the bipolar derivations.

IV. DISCUSSION

In the visual identification of seizure patterns on the neonatal EEG, some seizures patterns may be embedded in the signal but not obvious to the naked eye. These subtle patterns may be detected by a seizure detection algorithm. Arguably, automated single channel detection may potentially be superior to single channel human detection, particularly single channel aEEG. Examination of the per-patient results

TABLE II

SINGLE CHANNEL SEIZURE DETECTION RESULTS. TEST SET SEIZURE DETECTION PERFORMANCE FOR EACH BIPOLAR EEG DERIVATION. EI MULTI REFERS TO THE PREVIOUSLY REPORTED MULTI-CHANNEL EARLY INTEGRATION SEIZURE DETECTION ALGORITHM.

	EI Multi	C3-C4	C3-T3	C4-T4	F3-C3	F4-C4	C4-Cz	C3-Cz	C4-O2	C3-O1
Acc (%)	89.24	84.05	79.61	81.27	79.62	81.93	83.35	82.10	80.98	81.01
Sens (%)	33.17	40.85	33.35	34.74	42.85	36.52	38.78	40.64	34.74	39.13
Spec (%)	95.99	90.02	86.11	87.76	84.51	88.00	89.42	87.74	87.35	86.84
GDR (%)	81.03	90.77	82.66	89.34	86.49	86.67	88.31	86.85	87.53	83.04
FDR (%)	3.82	9.43	13.41	11.65	14.99	11.41	10.09	11.77	12.08	12.66
ROC area	0.82	0.80	0.69	0.72	0.72	0.73	0.76	0.74	0.72	0.72

TABLE III
INDIVIDUAL SEIZURE DETECTION PERFORMANCES FOR C3-C4 WHEN COMPARED TO MULTI-CHANNEL ALGORITHM. 'SEIZURES' REFERS TO THE NUMBER OF SEIZURE REMAINING AFTER ARTEFACT REJECTION.

		EI Multi		C3-C4	
#	Seizures	GDR (%)	FDR (%)	GDR (%)	FDR (%)
1	17	41.20	1.50	29.40	5.30
2	3	0.00	1.80	0.00	4.60
3	147	80.10	3.40	98.60	6.20
4	4	100.00	4.90	100.00	12.40
5	48	81.30	4.40	83.30	10.10
6	41	100.00	17.70	100.00	33.20
7	6	100.00	5.70	100.00	11.60
8	17	60.00	2.80	82.40	1.60
9	11	63.60	3.20	90.90	10.20
10	25	84.00	5.20	96.00	11.70
11	13	53.80	1.60	84.60	9.20
12	2	100.00	3.60	100.00	12.80
13	25	96.00	1.80	100.00	8.50
14	1	100.00	6.90	100.00	18.00
15	4	100.00	5.30	100.00	19.90
16	31	94.40	1.80	86.20	0.60
17	11	90.90	1.10	81.80	2.70
Mean		79.14	4.28	84.31	10.51
Total	400				

in Table III shows that the overall seizure detection performance for the EI multi-channel algorithm is superior to the single channel algorithm for channel C3-C4. The single channel algorithm undoubtedly fails to identify some seizures due to topographic restrictions on the number of channels used. Identification of at least one seizure in all patients is beneficial however as it can provide the necessary evidence for the administration of antoconvulsant therapy in an individual patient. Table III shows that the single channel algorithm and the multi-channel algorithm missed all seizures for patient 2. Examination of the seizures for this patient shows that each of patient 2's seizures are focal and manifested mainly on electrode C3. A single bipolar channel of EEG has been found to compare favourably to a full montage of EEG in the automated detection of neonatal seizures. Single channel automated seizure detection in the NICU may offer a significant improvement over the more commonly used aEEG.

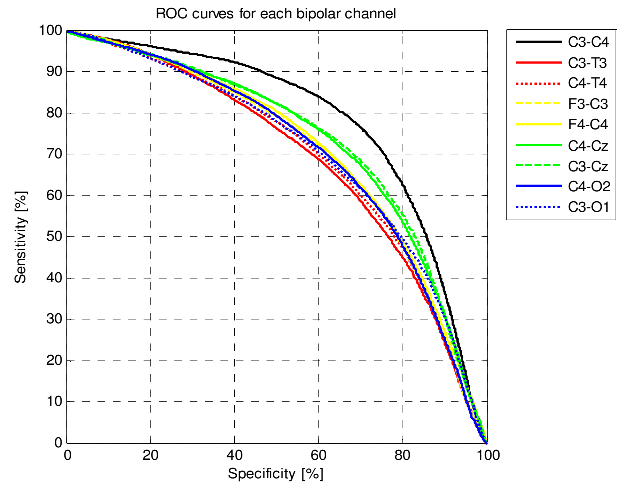

Figure 1: ROC curves for each EEG channel. ROC area for channel C3-C4 is 0.80.

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