DETECTION OF SEIZURE SIGNALS IN NEWBORNS

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ABSTRACT

This paper considers a system design for processing a multidimensional biomedical signal formed by EEG, ECG, EOG and motion recorded from a newborn, for the purpose of detection of epileptic seizures in newborns as an extension of the method reported in [1, 8]. We describe the proposed design, and discuss how the signals will be analysed and fused to detect the occurrence of seizure. We also discuss the role of modelling in refining the signal processing unit.

1. INTRODUCTION

Neurological disease or dysfunction in humans is often first indicated by epileptic seizure in newborns. Prolonged seizures, without appropriate action can result in impaired neurodevelopment or even fatality. In adults, the clinical symptoms of seizure are well defined (most noticeably uncontrollable repetitive or jerky movement of body or body parts); however in newborns the symptoms are easily missed without close constant supervision (manifests as slight facial characteristics including sustained eye opening with ocular fixation, repetitive blinking of eyelids, drooling and sucking).

A seizure is defined to have occurred when an abnormal excessive synchronous discharge of neurons occurs within the central nervous system. Such discharges can be detected in EEGs (electroencephalograms), with the main indicator being the presence of repetitive paroxysmal events. In adults and children, sharp EEG transients (SETs) usually indicate interictal (between seizure) EEG and an epileptic process. However, the problem of detection is significantly more complicated in newborns than in adults, since SETs are commonly present in the EEG of both neurologically normal newborns, and those with epileptic tendencies. The EEG signal also varies significantly from patient to patient, and depends significantly on the conceptual age of the newborn.

The EEG alone is insufficient for a neurologist to diagnose a patient. The diagnosis of seizures in newborns, often also requires examination of ECG (electrocardiogram) and EOG (electro-oculogram) signals, along with patient observation records. This is a time consuming and labour intensive process. The ultimate goal for research in this field is to produce a real–time automatic system for monitoring of newborns, using all of the various available signals, to make a decision as to whether seizure has occurred, thus relieving expert staff for other tasks. We present an outline for designing a multidimensional signal processing system for monitoring of seizure detection.

2. SIGNALS ACQUISITION

The development of an automated system to detect and classify seizures in the EEG of newborns is proposed for automatisation of the evaluation process used by neurologists. This requires the use of ECG, EOG and video signals. The conjugate analysis of these signals will allow the rejection of artefact features in the EEG signal that prevent accurate classification of seizure events.

EEG signals are measured by using electrodes attached to the skin of the newborn (Ag-AgCl electrode flushed with conductive gel adhered by tape). The wires attached to the electrode that transmit the signals act as antennas, such that the variability in the skin-electrode interface ($Z \sim 25k\Omega$) between patients is found to be less significant than noise pollution concerns. The EEG signal ($10 \sim 20\mu V$) is contaminated by the environment of an intensive care ward which is rich in electromagnetic emanations (AC noise in life support equipment and lighting; bioelectric fields of nursing staff). AC noise (Australia - 50Hz) is eliminated from the observation band (usually $f \leq 100$Hz) by using a bandstop filter or a filter with a roll-off below the AC frequency; however, pollution of the EEG signal through handling or disruption of the sensor position with respect to the signal and noise sources (motion of the baby) is not frequency specific. On occasion, these pollution sources produce artefacts in the signal that closely resemble actual seizures and have to date hindered the development of very accurate automated classification systems.

The proposed multidimensional signal approach uses EEG, ECG, EOG and video signals to assist in the removal of artefacts from the EEG signal.

The ECG signal ($\sim$10mV) is approximately 1000 times stronger than that of an EEG. Electrodes used to measure EEG signals are sensitive to this significant electrical signal, which is present in the body wherever arteries may be found, such as in the brain. This signal is often displayed as a noise component in the background of a neonatal EEG. The monitoring of the ECG signal allows for the removal of this noise component, showing a distinct pattern, from the EEG.

The EOG monitors eye movement; that is, eyes opening and closing. Eye movement also produces electrical activity on the scalp due to muscle firing and thus interferes with the EEG. The signal from the EOG is expected to contribute a measure of environmental conditions (ie. motion of staff in the near field of the baby's vision) and physiological responses to seizures (ocular fixation, REM etc.). The EOG is used to determine the state of the baby, which is important in EEG analysis. There are five neonatal behavioural states, of which only the first three are regarded as practical for routine clinical EEG:

State	Eyes open	Regular Respiration	Gross Movement	Vocal
1	no	yes	no	no
2	no	no	yes	no
3	yes	yes	no	no
4	yes	no	yes	no
5	yes	no	yes	yes

Artefacts associated with the motion of the baby are removed through the analysis of video signals which record the motion of the babies and any interference to the sensor environment caused by handling of the babies. Spasmodic muscle contraction associated with seizures may be investigated by both video motion detection and EOG data.

The proposed method combines the information from EEG, ECG, EOG and video signals to improve the accuracy of the automated detection scheme previously proposed by one of the authors and co-workers [1, 8]. To our knowledge this is the first attempt to integrate all four of these signals into an automated detection scheme.

3. SYSTEM DESCRIPTION AND DATA FUSION

In our proposed method there will be 5 dimensions (ie. 5 input signals). These will be EEG[1] $\times 2$, ECG, EOG and Motion (video signal). Due to the noncommensurate nature of the signals, they cannot be combined directly, but must be combined at the feature/state vector or decision level. Thus each signal will be initially processed separately to extract the features required for the decision. This is outlined in the block diagram in figure 1.

The signal processing unit is required to transform the signal to a form more suitable for the data fusion in the decision making unit. For the current problem, each signal should ideally be characterised by a set of suitable parameters provided by signal modelling. The signal processing unit will provide the decision making unit with all of the parameters (the state vector) it requires to make the decision whether a seizure is occurring (1) or not occurring (0).

The production of this indicator will require the establishment of a set of rules that specify the importance and role of each signal in the decision making formula. In brief, the EEG signal, which is the primary signal, will be evaluated to measure spectral content of normal and seizure activity in the neonate. The role of the EEG is discussed further in 4.1.

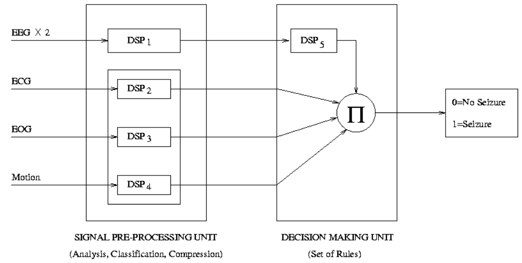

Figure 1: Block diagram of proposed detection system. The Signal Pre–Processing unit will extract features from the raw signals. The Decision Making Unit determines if the EEG signal is ictal based on the parameters from the processing. The remaining signals are then used to determine if the detection should be rejected due to possible artefacts.

The role of the motion/video signal is to detect the movement of the baby, or the presence of another party and to eliminate false alarms likely to result from these events. Ideally, the difference between the two events should be distinguished. The signal processing would be expected to provide information regarding the amount of detected movement, separating that inside the crib (baby) from that outside (others).

The primary purpose of ECG and EOG signals is to remove artefacts from the EEG. Interference from ECG and EOG has long been observed, and schemes for their removal proposed (for example Witte et al [9]). The EOG signal will also play an important role in determining whether the patient is in REM (Rapid Eye Movement) or NREM (Non-REM) sleep, which will be important in the decision process, as EEG signals are effected by the state of the patient.

4. THE SIGNAL PRE-PROCESSING UNIT

The main task of the signal processing unit will be to characterise and extract critical features from the input signals, and to provide these to the decision making unit. The signal processing unit is composed of several specialised subsystems processing EEG, ECG, EOG and video signals in parallel.

4.1. The EEG Signal

Of the four types of signals used, the EEG contains the core information needed for detecting seizures. Detection of seizure in newborn EEG requires classification of the various signal types present in EEG, itself requiring a good understanding of the physiological origins of EEG and how they relate to seizure.

The patterns found in EEG signals of newborns are in general of two types, background[2] or paroxysmal[3]. The

[1] Paired electrodes will be used to measure EEG signals in the left and right lobes. The size of the patients limits the collection of EEG to two pairs.

[2] Care should be taken throughout the literature as background can mean either (i) nonictal or (ii) without transient behaviour. We use the second definition here.

[3] The definition of paroxysmal implies pertaining to a sudden attack of a disease. This is an unfortunate terminology from adult EEG, where transients with such morphology are ictal.

background EEG is the predominant spectral rhythms of the EEG and is always considered normal. Paroxysmal events have sudden onset and termination, with amplitudes higher than the background. As previously stated, seizures are manifested in repetitive periodic paroxysmal events that evolve in amplitude and frequency before finally decaying. However, in newborns paroxysmal events are not all necessarily ictal (associated with epileptic seizure). Thus paroxysmal events are separated into three groups, (i)normal for the conceptual age; (ii)ictal, which are always abnormal; (iii) abnormal but not necessarily ictal.

Spurious artefacts from both equipment and physiological origins may also appear as paroxysmal events in the EEG and include muscle artefacts, electrode popping, eye movement, sweating, vascular artefacts, swallowing and respiration, sobbing and sucking tremor.

In essence the problem with newborn seizure detection using EEG is that there is significant overlap between the spectral characteristics of both ictal and nonictal (normal) EEG.

The design of an automated detection system which accounts for all of the mentioned paroxysmal events and artefacts, first requires physiological models of these signals to be obtained.

4.2. Principles of EEG Signal Modelling

MacGregor and Lewis [4] consider all models of the brain with respect to a stratification of variables for EEG modelling such as: (1) Behaviour, consciousness; (2) Electrical signals and chemical secretions; (3) Cellular neurophysiology; (4) Molecular processes. Models should ideally relate two or more adjacent strata.

Models of the EEG signal may be classified into levels:

1. frequency analysis to describe EEG signals (not really modelling);
2. modelling populations of cells and the relation to the EEG signal.

Further levels include spatial and temporal modelling of the signals production. Each successive level includes a greater understanding of the actual origins of the EEG signal, and a more holistic view of the brain. In the case of EEG, many previous workers have not gone beyond level 1, with little or no physiological basis for analysis.

Each level of modelling is now briefly described, and their potential weaknesses or strengths discussed.

4.2.1. Level 1 models

This level of modelling is often called nonparametric modelling. This level of analysis seeks to characterise the observed EEG signal through frequency decomposition, the goal being to extract spectral features. There is no attempt to relate particular rhythms to their physiological source, and hence model parameters are unrelated to the underlying physical processes. There may however be an attempt to correlate certain events or rhythms with various patient behaviours, such as seizure. This level of "modelling" (perhaps more correctly classed as description or analysis) is essentially a "black–box" approach to the brain.

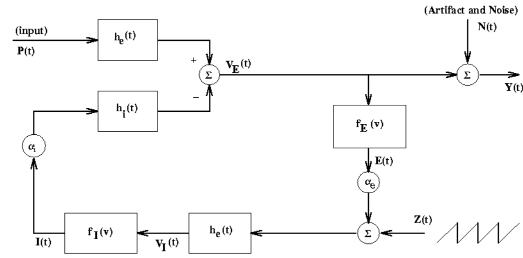

Figure 2: A model for the generation of seizure EEG.

Although such analysis is often useful for understanding the properties of EEG, at present detection schemes based on such analysis are questionable because as stated earlier, there is significant overlap of spectral features between ictal and nonictal EEG.

An example of such a detection scheme based on such an approach has been used by Gotman et al [3]. They make a comparison of the EEG signal spectrum with a reference spectrum from an EEG portion sixty seconds earlier. Detection is declared if the frequency, amplitude and width of the dominant peak of the spectrums are sufficiently different. These parameters are not related to any physiological process in an obvious way.

The main problem of such a detection scheme is that it does not account for the nonstationary nature of the EEG data spectrum. Such procedures may be adequate only for detection of seizure in adults and children where the overlap of spectral characteristics of normal and ictal EEG is less significant, and the EEG signal is more stable.

4.2.2. Our proposed model: a level 2 model

Level 2 models have a physiological basis, and generally relate the strata labelled 2 and 3 above. These models attempt to relate EEG signals to their physiological origins in populations of neurons. Parameters of the model generally define physiologically meaningful quantities. As a consequence it is expected that such models better reflect real EEG.

An example of a physiologically based parametric model is the model of the alpha rhythm of the thalamus of Lopes da Silva et al [2], which was extended by one of the authors and co-workers [5, 7, 6, 1, 8] to include seizure EEG.

The model considers a population of interconnected neurons, driven by a random input (in this case white Gaussian noise, with zero mean and standard deviation estimated from the EEG data) which is assumed to originate from deeper brain structures such as the thalamus and brain stem. The parameters of the model represent physiological characteristics such as neuronal interconnectivity, synaptic pulse response, and excitation threshold. The neuron population is modelled as a neuronal circuit consisting of both excitatory and inhibitory neurons. The mass synchronous discharge of neurons associated with seizure is modelled by a second input of a random repetitive waveform which drives the discharge. This input is modelled as the output of a linear pulse shaping filter driven by a random pulse train. This model is shown in figure 2.

Such a model is able to account partly for the nonstationarity of EEG signals, through adjustment of model parameters. These parameters are estimated from the EEG being examined, not a previous segment as used by Gotman et al. However, although seizure is included in the current model, better understanding of the driving mechanism may allow more realistic integration of this process into the model. In this model, the possibility of random nonictal SETs is not included.

5. DETECTION METHODOLOGY

Roessgen, Zoubir and Boashash [5, 7, 6, 1, 8] presented a detection scheme based solely on EEG, using the model described above. They demonstrated that such a model based approach outperforms an approach based simply on frequency decomposition (level 1 analysis).

Model parameters are estimated from the input EEG signal, with details of the estimation process given in [7, 8]. From these parameters, the integrated seizure EEG spectral estimate, $\hat{S}_{\mathrm{Seiz}}(\lambda)$, and the integrated background EEG spectral estimate, $\hat{S}_{\mathrm{Backg}}(\lambda)$, can be estimated.

Seizure detection is based on the statistic, $\hat{\Gamma} = \hat{P}_{\mathrm{S}}/\hat{P}_{\mathrm{b}}$ where

$$\hat{P}_{\mathrm{b}} = \sum_{k=0}^{N-1} \hat{S}_{\mathrm{Backg}}(\lambda_k),\ \hat{P}_{\mathrm{S}} = \sum_{k=0}^{N-1} \hat{S}_{\mathrm{Seiz}}(\lambda_k), \qquad (1)$$

and $\lambda_k = 2\pi k/N, k = 0, \pm 1, \cdots, \pm(N-1)$. The test for seizure is

$$\hat{\Gamma} \underset{H_1}{\overset{H_0}{\gtrless}} \gamma \qquad (2)$$

where H_0, the null hypothesis, is stated to be that seizure has occurred and the alternative, H_1, is stated to be that seizure did not occur, and γ is the threshold. The threshold γ is decided using tables, which are calculated theoretically or by simulation using real data, indicating the probabilities of missing seizure events and of false alarms.

The decision making unit firstly uses this method of classification based on the EEG, to determine a result which is confirmed or rejected based on the analysis of the other three signals, as indicated in the decision making unit part of figure 1. The decision making unit is required to determine:

1. if the ECG, EOG and motion indicate that the baby is in behaviour states 4 or 5;
2. if the EEG feature correlates with an ECG feature, indicating an ECG artefact;
3. if the EEG feature correlates with an EOG feature, indicating an EOG artefact;
4. if gross motion or handling is detected, indicating an equipment artefact.

If any of 1–4 is found to be true, then the detection is rejected as a false alarm. The set of rules is derived from standard medical methodology and the critical features extracted from corresponding models of EEG, ECG, EOG, motion and their correlations.

This set of rules will be expanded and refined once more information on the ECG, EOG and motion signals becomes available from future advances in signal modelling.

6. CONCLUSIONS

Various schemes have been proposed for the detection of epileptic seizures using EEG, particularly for adults and children. The problem in newborns is more complex, and the integration of other relevant signals is needed for seizure detection. Here we have presented a design for automatic monitoring system for seizure detection in newborns using a multidimensional signal comprised of EEG, ECG, EOG and motion signals. We propose to revise and extend the current EEG model in the future.

7. ACKNOWLEDGEMENTS

The authors wish to thank Prof Paul Colditz and Kimble Dunster from the Royal Women's Hospital, Brisbane, and Dr Bouchra Senadji from SPRC for providing useful technical details on data acquisition.

8. REFERENCES

[1] B. Boashash, A. M. Zoubir, and M. Roessgen. Online detection of seizure in newborn EEG using signal processing tools. In Proceedings of IEEE International Conference on Digital Signal Processing, Santorini, Greece, July 1997.

[2] F. H. Lopes da Silva, A. Hoeks, H. Smits, and L. H. Zetterberg. Model of brain rhythmic activity: The alpha–rhythm of the thalamus. Kybernetik, 15:27–37, 1974.

[3] J. Gotman, J. Zhang, J. Rosenblatt, and R. Gottesman. Automatic seizure detection in newborns and infants. In EMBC95, CD, 1995. paper 4.2.5.9.

[4] R. J. MacGregor and E. R. Lewis. Neural Modeling. Plenum Press, New York, 1977.

[5] M. Roessgen and B. Boashash. Seizure analysis of newborn EEG using a model based approach. ICASSP'95, Detroit, USA, 5:1936–1939, 1995.

[6] M. Roessgen and B. Boashash. A comparison of two techniques for detecting seizures in newborn EEG data. ICASSP'96, Atlanta, USA, 3:3101–3104, 1996.

[7] M. Roessgen, A. M . Zoubir, and B. Boashash. Seizure detection of newborn EEG using a model based approach. In Franklin T. Luk, editor, Advanced Signal Processing Algorithms,, volume 2563 of Proceedings of SPIE, pages 101–112, 1995.

[8] M. Roessgen, A. M. Zoubir, and B. Boashash. Seizure detection of newborn EEG using a model based approach. IEEE Transactions on Biomedical Engineering, 45(6):673–685, 1998.

[9] H. Witte, S. Glaser, and M. Rother. New spectral detection and elimination test algorithms of ECG and EOG artefacts in neonatal EEG recordings. Medical and Biological Engineering and Computing, 25:127–130, 1987.