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DESIGN OF A DSP SYSTEM FOR AUTOMATIC DETECTION OF SEIZURE SIGNALS IN NEWBORNS

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ABSTRACT

This paper considers the problem of processing EEG, ECG, EOG and motion signals recorded from a newborn, for the purpose of detection of epileptic seizures in newborns. We describe the proposed approach, and discuss how the signals will be analysed and combined to detect the occurrence of seizure.

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 whereas in newborns, clinical symptoms may be confused with normal behaviour.

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 approach for designing an automatic signal processing system for monitoring of seizure detection.

This paper updates the contribution presented in [1].

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 reason for this is that electrical activity measured by these signals (ECG, EOG) or impedance variations caused by movement (video) may contaminate the EEG recording. An example of this phenomena is shown in figure 1. The strong negative peaks in the EOG correspond to electrical activity in the muscles around the eye during blinking. The EEG electrodes measure electrical activity on the scalp, which is continuous with the skin around the eye. The contamination of the desired EEG signals by artefacts presents a significant problem for the automated detection of seizure. The pattern of peaks in the EEG, seen in figure 1, is similar to that of delta band (0.5–3.5Hz) seizure activity common to neonates. The combined analysis of these signals is intended to allow for 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. The skin–electrode interface formed is subject to inter–patient variability in the impedance and noise pollution concerns (especially AC noise generated by electrical equipment in intensive care units). In addition, variations in the impedance of the skin–electrode interface arise if the patient moves, stretching the skin and adjusting the capacitance of the contact. Of equal concern are corruptions of the EEG signal introduced by electrical activity of the newborn baby. The ECG (electrical

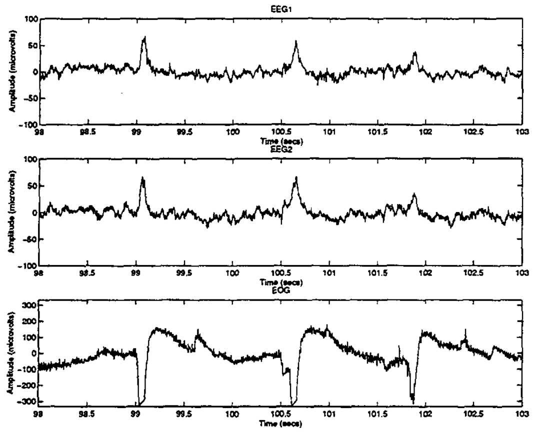

Figure 1: *EEG (top two frames, positive peaks) and EOG (bottom frame, negative peaks) signals showing artefact corruption. The EEG, that measures electrical activity at the surface of the skin, is sensitive to electrical activity in the muscles around the eye, the signal measured by the EOG. Here, the pattern of peaks caused by blinking, has a frequency similar to that of delta band (0.5-3.5Hz) seizure.*

activity in the heart of newborns) and EOG (electrical activity around the eye) are both potential sources. These signals, which have larger magnitudes, may corrupt the neonatal EEG signals.

Of the mentioned influences on signal quality, AC noise is the only source that can be readily removed using standard signal processing techniques. Bandstop or low–pass filters are used to remove AC noise from neonatal EEG. Impedance discontinuities and corruption from biological sources cannot be treated using this technique. This then motivates the use of a multidimensional approach[1].

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 [2, 7]. To our knowledge this is the first attempt to integrate all four of these signals into an automated detection scheme.

3. SYSTEM DESCRIPTION

In our proposed method there will be 5 dimensions (ie. 5 input signals). These will be EEG[2] ×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 2.

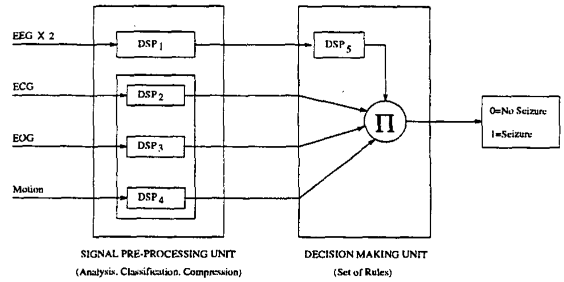

Figure 2: *Block diagram of proposed detection system. The Signal Pre–Processing unit will extract features from the raw signals. The Decision Making Unit determines if the EEG signal is ictal based on the parameters from the processing. The remaining signals are then used to determine if the detection should be rejected due to possible artefacts.*

The 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.

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 [8]). The EOG signal will also play an important role in determining whether the pa-

[1] The interested reader is referred to [1] for a more detailed description of technical aspects of neonatal EEG signal acquisition.

[2] 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.

tient 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*[3] or *paroxysmal*[4]. The 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.

[3] 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.

[4] 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.

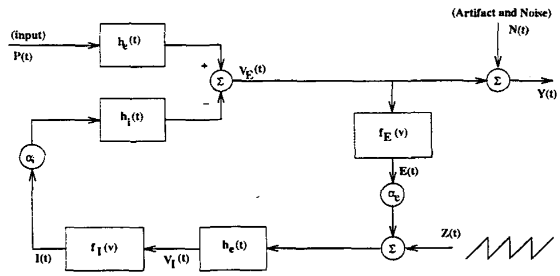

Figure 3: *A model for the generation of seizure EEG. A physiological basis is used in the formulation of the model. A simulated neuron population, with inhibitory and excitatory neurons, is driven by a shaped random pulse train to produce a seizure waveform.*

4.2. The proposed model

The principles of EEG signal modelling applied to this problem been previously discussed by the authors in [1].

The model of the alpha rhythm of the thalamus of Lopes da Silva et al [3], which was extended by one of the authors and co-workers [4, 6, 5, 2, 7] 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 3.

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 [4, 6, 5, 2, 7] 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 line-break frequency decomposition.

Model parameters are estimated from the input EEG signal, with details of the estimation process given in [6, 7]. From these parameters, the integrated seizure EEG spectral estimate, $\hat{S}_{\text{Seiz}}(\lambda)$, and the integrated background EEG spectral estimate, $\hat{S}_{\text{Backg}}(\lambda)$, can be estimated.

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

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

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 2. The decision making unit is required to determine:

1. if the EEG feature correlates with an ECG feature, indicating an ECG artefact;
2. if the EEG feature correlates with an EOG feature, indicating an EOG artefact;
3. if the video shows activity indicating an electrode artefact.

If any of 1–3 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

The problem of detecting epileptic seizures using EEG, requires the integration of other relevant signals such as ECG, EOG and video. This paper presented an approach for automatic monitoring system for seizure detection in newborns using a multidimensional signal comprised of EEG, ECG, EOG and motion signals.

7. ACKNOWLEDGEMENTS

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