EEG 'DIARIZATION' FOR THE DESCRIPTION OF NEONATAL BRAIN INJURIES

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ABSTRACT

Automated analysis and grading of the neonatal EEG has a potential to assist clinical decision making for neonates with hypoxic-ischemic encephalopathy. This paper proposes a method to grade the degree of abnormality in hour-long segments of neonatal EEG. The HMM-based speaker diarization approach is employed to segment and cluster the neonatal EEG into homogeneous states. Several features are proposed to characterize the resultant state sequence to provide a single measure for a complete hour-long EEG recording. These features aim at capturing both the statistics of the state durations (e.g. average state duration, average number of segments), and any patterns contained in the sequentiality of the obtained states (e.g. permutation entropy, entropy rate). Statistical analysis indicates that the proposed features contain discriminative information for the task of automated neonatal EEG grading. Unlike other studies, the developed framework of the EEG 'diarization' provides an easy and intuitive interpretation of the computed features, which is a clinically important aspect.

Index Terms— Brain injury, neonatal, hypoxic-ischemic encephalopathy, electroencephalography, grading.

1. INTRODUCTION

A lack of oxygen and impairment to the blood supply in the neonatal brain around the time of birth are some of the main causes of neonatal neurological morbidity [1]. Visual interpretation of background EEG, typically over an hour, by an experienced neonatal neurophysiologist allows an estimation of the degree of the occurred injury and timely treatment, such as the use of therapeutic hypothermia (cooling) [2]. This expertise is not continuously available in many neonatal intensive care units (NICU). Automated analysis and grading of the neonatal EEG has a potential to assist clinical decision making for neonates with hypoxic-ischemic encephalopathy.

Automated analysis of neonatal EEG has primarily focused on the detection of neonatal seizures [3, 4]. Several methods have been developed to grade background EEG in the paediatric and adult populations [5]. In contrast, in neonates only single elements of the complete grading system have been investigated so far, such as the detection of sleep stages or burst suppression patterns [6].

More recently, a neonatal EEG grading system has been developed in our group [7]. It incorporates a set of energy-based features [8, 9] to differentiate between EEG grades. Fig. 1 shows a clean and obvious example of EEG for various degrees of HIE injury. It can be seen that morphological and amplitude background patterns change gradually from Grade I to Grade IV.

In this work, a method to segment and cluster the neonatal EEG into homogeneous states is proposed based on the HMM speaker diarization approach. Several features are computed from the resultant state sequence to provide a single measure for a complete EEG recording. These high-level features are used to discriminate between EEG grades.

2. EEG DIARIZATION SYSTEM

2.1. EEG grading system overview

The EEG grading system flowchart is presented in Fig. 2. The core of the system is the diarization program *shout_cluster* from the SHoUT large vocabulary continuous speech recognition toolkit [10, 11]. As a proof of the concept, the toolkit is used here unmodified. In order to match the requirements for the application of the diarization algorithm, the EEG is passed through a phase vocoder. In audio, this allows for the slowing down of the playback of the waveform while preserving the original voice characteristics.

The adaptive segmentation and clustering of the EEG is then carried out to produce a sequence of EEG states over the recording. Various features are extracted from the resultant state sequence. The main aim of the work is to explore the new feature space based on the segmented EEG. For this reason, no classifier is implemented in this work.

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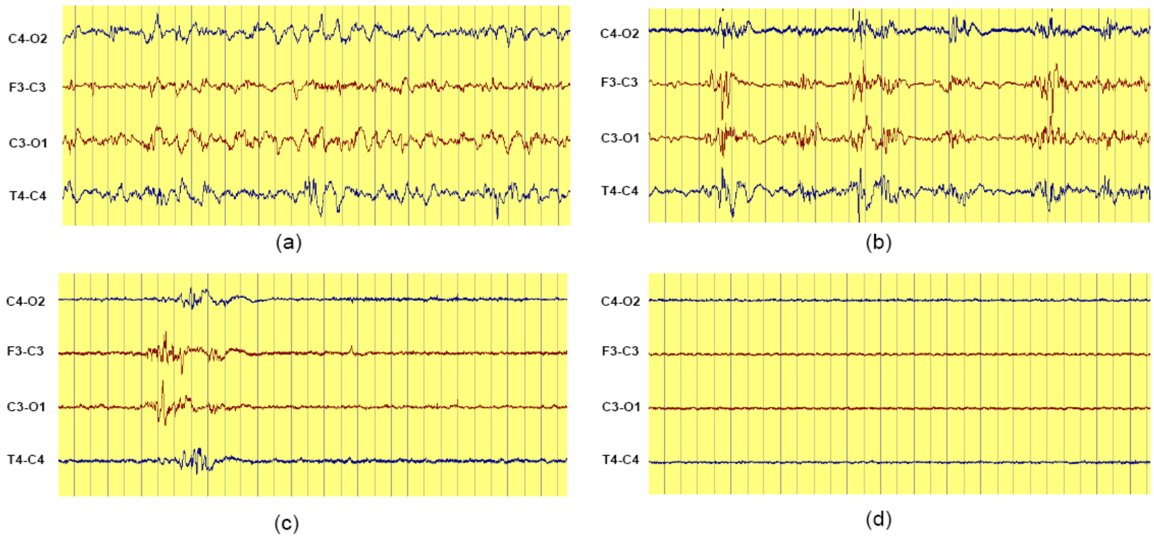

Fig. 1. Examples of *ideal* EEG segments affected by HIE. (a) Grade I: Normal/mild abnormalities, (b) Grade II: Moderate abnormalities, (c) Grade III: major abnormalities, (d) Grade IV: Inactive

2.2. EEG audification algorithm

The neonatal EEG is first audified using a phase vocoder [12, 13] to allow for the application of the *shout_cluster* diarization program without any modification. Specifically, the EEG is downsampled from 256Hz to 32Hz with an anti-aliasing filter set at 12.8Hz. The EEG activity of interest in neonates is negligible in frequencies over 16 Hz. Then, the EEG is passed through the phase vocoder to slow it down by a factor of 500. This process changes the temporal characteristics of a signal while retaining its short-time spectral characteristics; this intuitively corresponds to stretching the time-base of a signal spectrogram. The EEG is then saved with a 16 kHz sampling frequency which is required by the diarization algorithm. This corresponds to the frequency mapping of the original range of [0.5-16] Hz to the new range of [0.5-8] kHz. As a result, 1 hours of audio is produced from 1 hours of EEG.

2.3. Diarization algorithm

The selected diarization system has shown the state-of-the-art performances in the NIST RT evaluation in speaker diarization over a number of years [10, 14]. In this work we will refer to an EEG 'state' as equivalent to a 'speaker' in speaker diarization.

The diarization algorithm uses Gaussian mixture models as probability density functions to model each EEG state. The hidden Markov model is used to assign the frames to the corresponding EEG state. Fig. 2 presents the steps of the algorithm. During initialization, the EEG data is randomly split over a number of clusters. A large number of models are initially created. This set of models is then used to re-segment the EEG data. The agglomerative clustering reduces the number of models by merging the two most similar clusters as determined by a distance metric, the Bayesian information criterion. BIC compares the sum of likelihoods of two models obtained with their own data with the likelihood of a third model that is trained and evaluated on the concatenated data. A relaxed formulation of BIC is used by fixing the complexity before and after merging. This is achieved by making the number of Gaussians of the merged model equal to the sum of the Gaussians of the candidates that are merged [15]. The updated set of models is then used to re-segment the EEG data. The EEG segmentation is obtained by performing a Viterbi search on the whole EEG recording. The minimum duration of 2.5s is imposed by using a string of 250 states to model each EEG state. This whole process is repeated iteratively, until cluster merging is no longer necessary.

For the purpose of diarization, short-term EEG characteristics are captured by the first 19 cepstral coefficients which are extracted using standard processing procedures. It has been shown that cepstral coefficients, which can be regarded as wide-band spectral slopes, can be

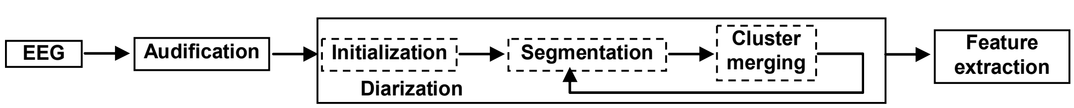

Fig. 2. A flowchart for the proposed neonatal EEG grading system

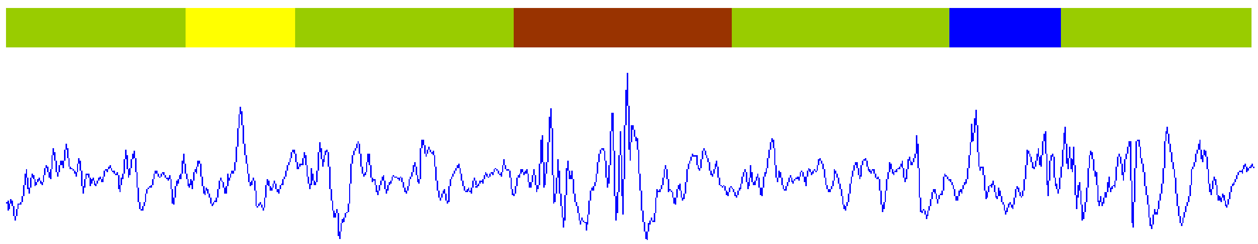

Fig. 3. An example of 25s of segmented and clustered EEG, with the distinct estimated EEG states superimposed on top.

equally discriminative in EEG signal classification [16].

2.4. Feature extraction

Several features are proposed to characterize the resultant state sequence to provide a single measure for a complete EEG recording. These features aim at capturing both the statistics of the state durations, state frequency, and any patterns contained in the sequentiality of the obtained states. For the general applicability of the developed EEG diarization, the features should be invariant to the recording length. The following features are computed with the number of features in parenthesis:

1. Duration-based (2). *Mean/Max duration* is calculated by taking the mean/maximum of the total duration of each EEG state across the whole recording. These features tend to show how much time is spent in each EEG state. The features are normalized by the total recording duration.

2. Frequency-based (2). *The number of segments* and *the number of distinct EEG states* are computed. The former indicates the frequency of alternating EEG states. The latter shows the level of diversity in each EEG recording. These are normalized by the number of minutes in the recording.

3. Sequence-based (2). For a sequence of states, *Y, the entropy rate* [17] is computed as

$$H(Y) = -\sum_{ij} \mu_i P_{ij} \log P_{ij} \qquad (1)$$

where μ_i is the prior probability of the i^{th} state and P_{ij} is the estimated transition probability from the i^{th} to j^{th} state. This feature quantifies the rate of information innovation in a sequence.

Permutation entropy [18] is defined as:

$$PE = -\sum_{i=1}^{M} P_i \log P_i \qquad (2)$$

Here it is assumed that we are looking at all M possible permutations of a sequence of m states, where $M \leq m!$, and m is referred to as the embedded dimension. P_i represents the probabilities of occurrence for the each sequence. As can be seen, this calculation is based on mapping the time series onto a symbolic sequence in order to quantify the relative occurrence of the different symbols. Permutation entropy is a quantitative measure of the local order structure complexity. The permutation entropy ranges from 1 (all permutations have an equal probability) to 0 (complete regularity). The smaller the value of the permutation entropy is, the more regular the time series is.

3. EXPERIMENTS AND DISCUSSION

3.1. Dataset

The dataset in our work is composed of EEG recordings from 54 newborns with HIE recruited from the NICU, Cork University Maternity Hospital, Cork, Ireland. The patients were full term babies ranging in gestational age from 39 to 42 weeks. Approximately one hour of EEG per baby, free of seizures and major movement artifacts, was selected from the recordings to ensure a relatively constant EEG grade was present within the segment. A Carefusion NicOne video EEG monitor was used to record multi-channel EEG at 256Hz using an 8 channel bipolar montage. As HIE is assumed to be a global injury, the information about the injury is carried equally by each EEG channel. Results from only one EEG channel are presented in this work.

3.2. Results

An example of segmented and clustered EEG is shown in Fig. 3 for a 25-second chunk of EEG from a patient with the Grade II HIE injury. It can be seen that the algorithm identified one main EEG state which is the most frequent one and several other distinct states of variable duration.

The computed features for the four EEG grades are shown in Fig. 4 where the feature mean and 95% confidence intervals are indicated for each group.

Looking at the duration-based features, it can be seen that, in general, lighter brain injury leads to longer homogeneous EEG segments. The *Max duration* feature indicates that a single EEG stage (accumulated over the recording) can cover on average 80% of the recording for Grade I and 25% for Grade IV.

Similarly, from the frequency-based characteristics, the lower *number of distinct states* and the lower *number of segments* per minute are indicative of a lower EEG grade.

Finally, the sequence-based parameters *permutation entropy* and *entropy rate* both show lower levels of regularity in the state sequences for higher EEG grades.

It is known that the most difficult grades to separate are Grade I and Grade II which can also be seen in Fig. 4.

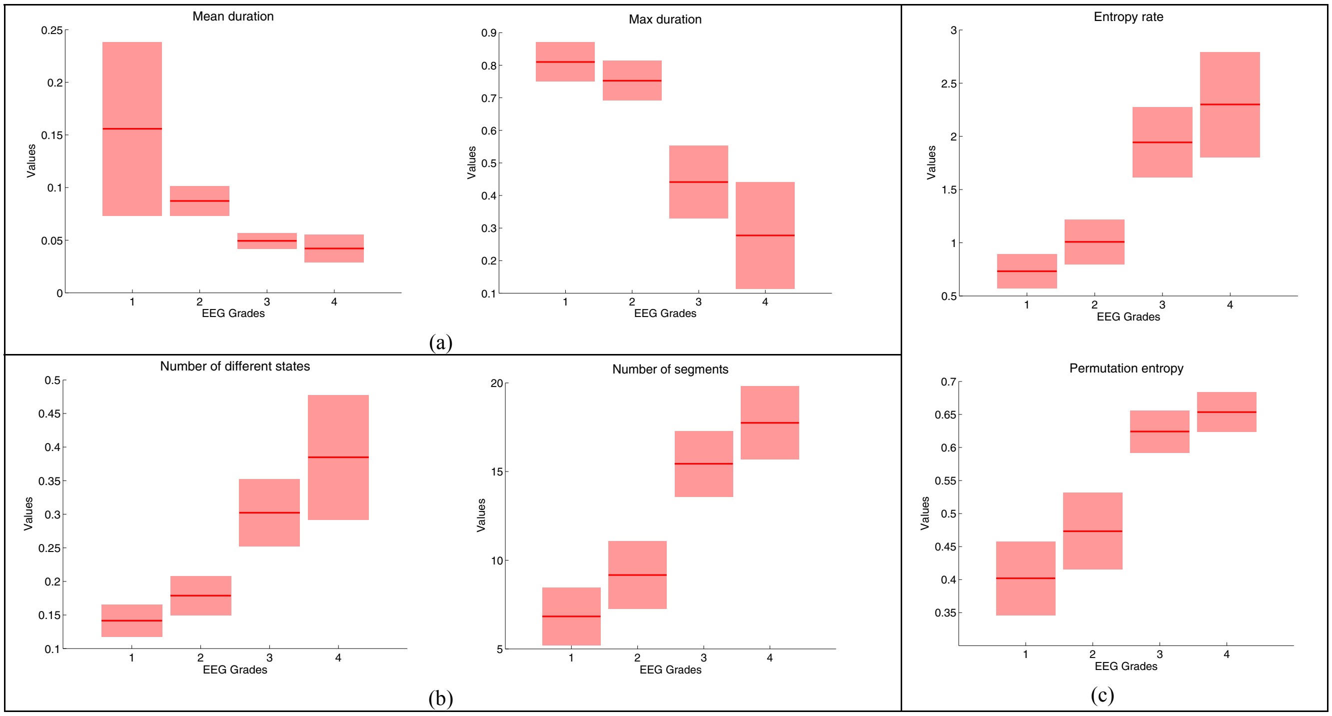

Fig. 4. (a) Duration-based, (b) frequency-based and (c) sequence-based features, their means and 95% confidence intervals for different EEG grades.

It was shown in [7-9] that energy and energy-based derivatives can lead to reasonably accurate EEG grading. In particular, the EEG grade 4 can be completely isolated from the other grades using only energy-based characteristics. In the proposed framework, signal energy is not exploited at any stage. As in speech processing, there are advantages and disadvantages of using energy-based features which are not discussed in this study.

Because the features are invariant to the recording duration, similar distributions can be expected for over-segmented or under-segmented sequences as long as a common stopping criterion is used for all EEG recordings.

4. LIMITATIONS AND FUTURE WORK

Currently, the audification settings are used to match the pre-set algorithmic parameters of the diarization algorithm such as analysis the window length, degree of smoothing, etc. Modification of the *shout_cluster* tool will allow a direct tuning of the internal parameters of the diarization algorithm and the redundant audification step can then be skipped, which will also significantly reduce the processing time.

The results presented here are obtained using only one EEG channel. The decision level statistical averaging of features across all available eight channels will reduce the distribution overlap among states. It is reasonable to explore the interdependencies between channels at a lower level than the decision level by considering feature vectors from each channel as separate streams in an integrated multi-stream HMM framework.

In this work, we use 19 cepstral coefficients as short-term spectral features. It has been shown [16] that while spectral slope features can be accurate for EEG classification, augmenting them with several conventional EEG features [19], in particular from the information-theory domain, leads to better EEG description.

5. CONCLUSIONS

In this work, the state-of-the-art speaker diarization algorithm was applied to neonatal EEG. Several features were extracted from the segmentation to characterize the resultant state sequence. It was shown that the statistics of the state durations, frequency and order carry discriminative information for the task of neonatal EEG grading. Unlike other studies, the proposed framework of EEG 'diarization' provides an easy and intuitive interpretation of the computed features, which is a clinically important aspect. We hope that this paper will inspire more research on EEG segmentation and clustering using diarization approaches developed in speech processing.

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