MODULATION FREQUENCY ANALYSIS OF SEIZURES IN NEONATAL EEG

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ABSTRACT

Detection of seizures in neonatal EEG signal represents a formidable challenge for clinicians in the neonatal intensive care unit (NICU). Seizure morphology is known to evolve both temporally and spatially with a similar evolution also observed in the frequency domain. The modulation frequency analysis which is widely used in speech processing is used here to extract the frequency-localized spectral dynamics of the neonatal EEG and investigate their discriminative capabilities in the context of neonatal seizure detection. This study suggests that the spectral dynamics of neonatal EEG are more informative than short-term spectral characteristics. It is shown that the seizure-relevant components of the modulation spectrogram are found in the vicinity of 0.4Hz. Modulation frequency analysis represents a new insight into the EEG signal which can uncover the underlying time-structural organization of the neonatal EEG signal and therefore improve clinical understanding of the dynamic processes involved.

Index Terms— Modulation frequency, neonatal EEG, neonatal seizures, epilepsy, electroencephalography.

1. INTRODUCTION

Multi-channel EEG, a technique that measures the electrical activity of the brain, is the most accurate test available for the detection of neonatal seizures. Most hospitals lack the special expertise required to interpret EEG, especially on a 24/7 basis and seizures therefore often remain undiagnosed. The availability of automated neonatal seizure detection algorithms in the NICU may help to provide a solution to this urgent clinical need.

A number of methods and algorithms have been previously proposed in an attempt to automatically detect neonatal seizures [1-7]. One group of studies follows analytical learning principles [8] and focuses on the creation of a set of heuristic rules and thresholds from clinical prior knowledge [1, 3, 4]. Another approach relies on inductive learning [8] and utilizes statistical classifier based methods [2, 5-7], which employ elements of machine learning to classify a set of features using a data-driven decision rule.

Automated seizure detection in the newborn using EEG is a challenging task. The difficulty arises from the relative rarity of this event of interest, the within-class variability of seizure waveform characteristics and several similarities in signal characteristics between seizure, artifact, and background EEG [9].

It is known that unlike background EEG or artifacts, seizure morphology evolves both temporally and spatially (Fig. 1). In fact, there is evidence to suggest that neonatal EEG is non-stationary, both on large and small time scales [10]. This nonstationarity includes longer duration changes in amplitude and frequency, as well shorter duration changes in frequency content within a single frame. In an attempt to account for the latter, a number of studies have investigated time-frequency analysis of EEG, substituting conventional Short-Time Fourier Transform (STFT) with non-stationary and non-linear techniques for feature extraction, such as quadratic time-frequency distributions, atomic decomposition, wavelets, etc [11-15]. Many researchers however still perform spectral analysis of sufficiently short segments of quasi-stationary EEG, describing 5-10s of the EEG signal. Similar to speech processing, the spectral envelope based characteristics such as filter-bank energies, edge frequencies, frequency centroids are well accepted as primary carriers of the identity of the given EEG signal segment [16].

The work presented in this paper addresses the medium-term nonstationarity in the neonatal EEG by considering the temporal evolution of the power spectrum as a carrier of discriminative information for the task of neonatal seizure detection. In particular, modulation frequency (MF) analysis [17-20] is used to extract the frequency-localized spectral dynamics of EEG. The discriminative power of this feature is investigated for neonatal seizure detection.

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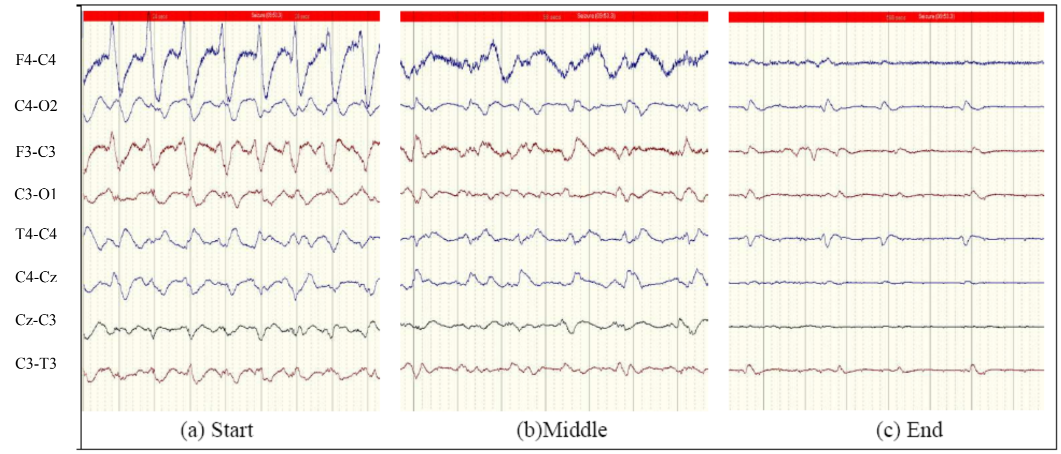

Fig. 1. Evolution of a single seizure event shown in three ~7-8s segments. (a) Slow wave activity at start with sharp/spike components involved, high in amplitude and frequency. (b) As the seizure progresses the EEG becomes lower in amplitude and frequency. (c) Only very low amplitude discharges are seen with a flattening of the background.

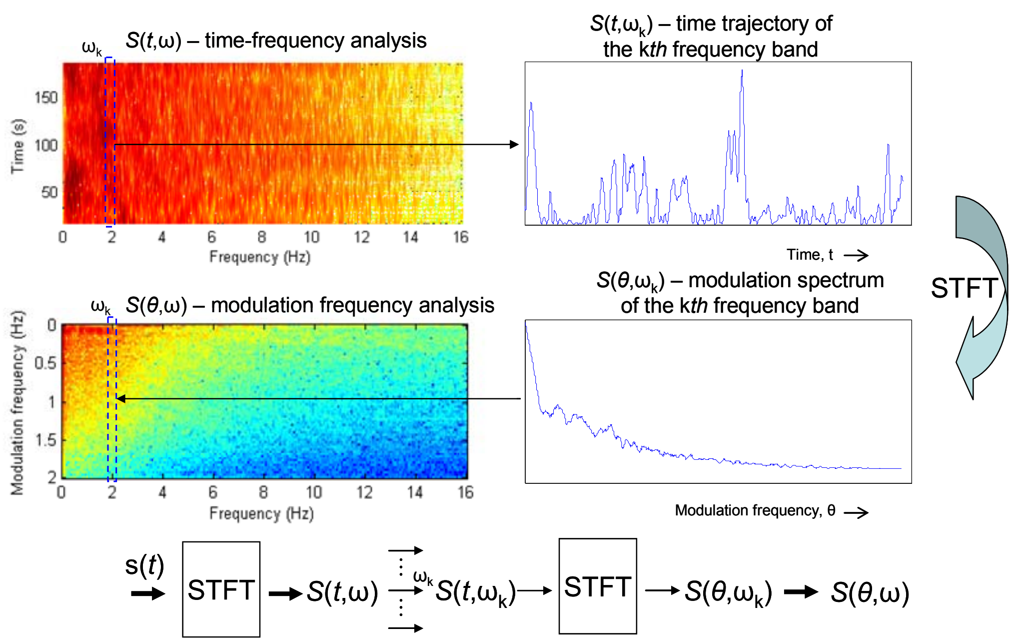

Fig. 2. Modulation spectrum of EEG obtained by the spectral analysis of the temporal trajectory of each power spectral component of EEG. The flowchart of the processing is shown below. Best viewed in color.

The work is organized as follows: Section 2 provides details of the MF analysis. Section 3 presents experimental results and discussion. Section 4 relates this work to prior studies. Conclusions are drawn in Section 5.

2. MODULATION FREQUENCY

MF analysis extracts frequency information over longer time spans in different frequency bands. The temporal energy fluctuations in speech have been well reported [19, 20]. It is know that the basic modulation pattern around the 4Hz range is a fundamental property of speech [17]. Unlike speech, to the best of our knowledge, MF analysis has never been applied to the neonatal EEG signal.

The basic architecture of MF analysis is illustrated in Figure 2. The EEG is down-sampled from 256Hz to 32Hz with an anti-aliasing filter set at 12.8Hz. It has been shown that frequencies of neonatal EEG seizures range between 0.5 and 13Hz and the dominant frequencies of seizures vary between 0.5 and 6 Hz [15]. As the lowest frequency of seizures is 0.5Hz, a 2s window is required to capture a single period of seizure activity. Since the seizure activity is defined as a repetitive waveform, the frame length should be at least twice the largest period of a seizure waveform. The STFT is thus performed every 0.25s on a window of 4s. Individual STFT energy magnitudes are consolidated into a smaller number of frequency bands by summing. The consolidated magnitude energies in each frequency band are then subjected to another STFT using a longer time window of 128s. A compression of $\log_{10}(1+|S(\theta,\omega)|)$ is applied to each MF to reduce the dynamic range. The resulting STFT values correspond to the MFs in each frequency band. The MFs in the range of 0 to 2Hz are investigated, for neonatal EEG frequencies in the range of 0.5 to 12Hz. The DC MF component of the signal is ignored.

3. EXPERIMENTS AND DISCUSSION

3.1. Dataset

The dataset in our work is composed of EEG recordings from 18 newborns recruited from the NICU, Cork University Maternity Hospital (CUMH), Cork, Ireland. The patients were full term babies ranging in gestational age from 39 to 42 weeks. A Carefusion NicOne video EEG monitor was used to record multi-channel EEG at 256Hz using the 10-20 system of electrode placement, modified for neonates. The standard protocol for EEG recording in the NICU required the following 9 active electrodes: T4, T3, O1, O2, F4, F3, C4, C3, and Cz. Then, the following 8 EEG bipolar pairs were used to annotate the data: F4-C4, C4-O2, F3-C3, C3-O1, T4-C4, C4-Cz, Cz-C3 and C3 - T3. All electrographic seizures were annotated independently by two experienced neonatal electro-encephalographers using simultaneous video EEG. The combined length of the EEG recordings of seizure patients totaled 816.7 hours (~6 million frames). The dataset contained 1389 electrographic seizures with an average duration of ~4 minutes. The dataset contains a wide variety of seizure types including both electrographic-only and electro-clinical seizures of focal, multi-focal and generalized types. The continuous EEG recordings were not edited to remove the large variety of artifacts and poorly conditioned signals that are commonly encountered in the real-world NICU environment. Therefore this dataset is truly representative of the real-life situation in the NICU.

3.2. Experimental setup and metrics

Each point on the modulation spectrogram represents the power of modulating a narrow-band EEG signal component with one modulation frequency. The time series of each point is scored against the trend of the ground truth, where ones and zeros are used to indicate the presence or absence of seizure in time. By varying the threshold on the energy of each point in the modulation spectrum, sensitivity and specificity are calculated which are defined as the accuracy of the seizure and non-seizure class, respectively [21]. This task is similar to that of speech activity detection, whereas in seizure detection, the area under the receiver operating characteristics curve (ROC area) is reported rather than the equal error rate [21]. The range of the ROC area is from 0.5 for no apparent distributional difference between classes, to 1 for perfect separation between classes [22]. Furthermore, the ROC area is equivalent to the Wilcoxon rank sum statistical test [23]. This can be interpreted as such: For a seizure detector giving a continuous value in the form of the MF energy, the ROC area quantifies the probability that a randomly sampled seizure epoch will have a higher energy than a randomly sampled non-seizure epoch.

In contrast to multi-channel speech processing, neonatal seizures can be completely localized to a single EEG channel with other channels carrying no sign of seizure activity. For this reason, each EEG channel is processed by the MF analysis separately. Then, the ROC area is computed for each channel. The maximum of the ROC areas across channels is reported. This procedure naturally limits the absolute metric value. When seizures migrate from one channel to another, none of channels will have good ROC on its own. However, the maximum ROC across channels will reveal if there were any MF-based signature of seizures in any channel, and this is the primary focus of this study.

3.3. Seizure dynamics

The discriminative capability of the MF spectrogram powers is given in Figure 3. The color intensity indicates the discriminative capability of each bin rather than its absolute value. As expected, it can be seen that not all temporal dynamics carry relevant discriminative information for the task of seizure detection. Still, relevant information can be discovered with the MF analysis with the highest discrimination achieved in the vicinity of the MF of 0.4Hz and the EEG frequency of 2Hz.

Interestingly, a certain seizure temporal structure can be perceived from Figure 3. There is a distinct shift of the most discriminative MFs across the EEG frequencies.

Figure 4 shows the performance of the conventional log power spectrum features within the same discriminative framework. For comparative purposes, these features were computed with the same spectral resolution as in the MF analysis but on 8s windows with 50% overlap – the standard feature extraction of the state-of-the-art neonatal seizure detection systems [5-7, 9]. Note that the best performance ROC = ~0.74 is much less than the ROC = ~0.84 achieved using the MF analysis. This seems to point to the fact that the EEG spectrum varies gradually over each segment. It also suggests that this temporal evolution (as detected by the MF analysis) is a more discriminative cue to the identity of a given segment than the spectral parameters themselves.

The MF analysis can be applied to uncover underlying temporal dynamics for other events of interest in the EEG. The parameters such as the lengths of the initial STFT and

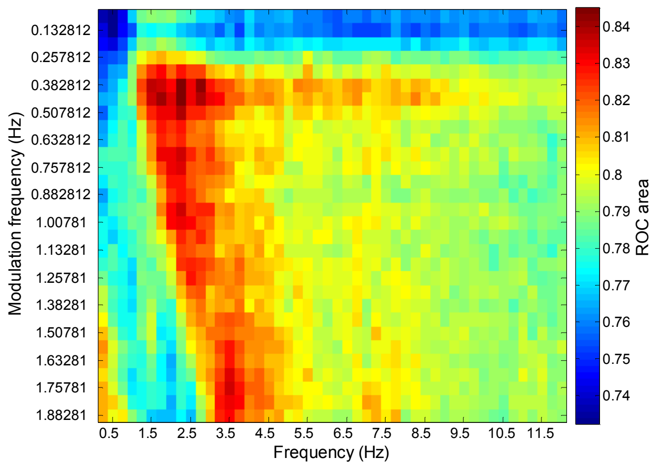

Fig. 3. Modulation spectrogram in the discriminative framework. Color intensity indicates the discriminative capability (ROC area) rather than the absolute energy value. Best viewed in color.

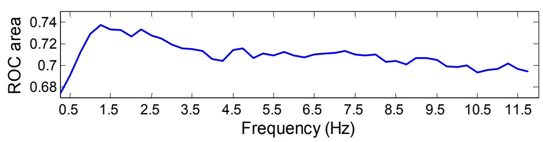

Fig. 4. The discriminative capabilities of conventional log power spectral densities for neonatal seizure detection.

the second longer SFTF transforms should be tuned accordingly.

4. RELATION TO PRIOR WORK

EEG-based biomarkers of Alzheimer's disease have been proposed in [24, 25] using the MF analysis applied on a shorter time scale (5s). Several cross-frequency MF patterns that were observed exclusively in the control group of healthy patients were highlighted in these papers. In contrast, the work presented in this paper addresses the medium-term dynamics in the neonatal EEG which were extracted from a time-span of 2 minutes.

The temporal dynamics within EEG for neonatal seizure detection at the level of the whole recording have been discussed in [29], where the distribution of seizures in time since birth was modeled and incorporated into the decision making. Event-long neonatal EEG dynamics have been investigated at the level of the probabilistic output of the classifier in [30] by computing the derivative of the seizure probability with respect to the adaptively-modeled probability of background. In contrast, this work deals with the medium-term EEG dynamics at the feature level.

MF analysis uses a magnitude and phase decomposition to separate frequency subbands into a carrier and a modulator. There are other amplitude-modulation frequency-modulation (AM-FM) decompositions of monocomponent signals. Other works assume similar time-varying amplitude and frequency models of the EEG, and propose methods to estimate their time-varying frequency component. While the present study is related to approaches in time-frequency analysis by Boashash et al [11-14], the dynamics of medium term time resolutions capitalize on a new feature space, which was not considered in these earlier studies.

The AM-FM decomposition is implicitly studied in research on instantaneous frequency estimation. The decomposition of the EEG into a low bandwidth signal that describes the amplitude modulation of the signal, and the instantaneous frequency as a carrier has been performed in [31] for determining the degree of brain injury in the newborn. Wideband signals typically contain multiple AM and FM components, which are inadequately described by a single modulator and carrier. This work specifically addresses frequency-localized spectral dynamics of neonatal EEG which has not been done before.

In our previous work [26], we have shown that short-term speech recognition features can be seen as spectral slope characteristics which are either wide-band (cepstral coefficients [27]) or localized in frequency (frequency-filtered parameters [28]) and can be equally useful in EEG signal processing for various classification tasks. In fact, it has been shown that the use of spectral slopes produced higher classification accuracy than simple filter-bank energies. In this work, another technique is borrowed from the area of speech processing and communication.

The authors believe that the features computed from the modulation spectrogram can provide complementary information to characteristics commonly used in EEG signal processing [32].

5. CONCLUSIONS

In this work, modulation frequency analysis was applied to neonatal EEG. The frequency-localized spectral dynamics of neonatal EEG were extracted and their applicability to the task of neonatal seizure detection was determined. In particular, the spectral dynamics of neonatal EEG were shown to be more discriminative than the short-term spectral characteristics. It was also shown that the seizure-relevant components of the modulation spectrogram were found in the vicinity of 0.4Hz. Modulation frequency analysis improves our understanding of the dynamic processes involved in the neonatal EEG and the signal structure revealed may be of interest to clinical neurophysiologists. The contribution of the new feature to the established systems of neonatal seizure detection will form part of our future work.

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