2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

An EEG analysis framework through AI and sonification on low power IoT edge devices

Sergi Gómez-Quintana, Grainne Cowhig, Marco Borzacchi, Alison O'Shea, Andriy Temko, *Senior Member, IEEE,* Emanuel Popovici, *Senior Member, IEEE*

***Abstract*— This study explores the feasibility of implementation of an analysis framework of neonatal EEG, including ML, sonification and intuitive visualization, on a low power IoT edge device. Electroencephalography (EEG) analysis is a very important tool to detect brain disorders. Neonatal seizure detection is a known, challenging problem. Under-resourced communities across the globe are particularly affected by the cost associated with EEG analysis and interpretation. Machine learning (ML) techniques have been successfully utilized to automate seizure detection in neonatal EEG, in order to assist a healthcare professional in visual analysis. Several usage scenarios are reviewed in this study. It is shown that both sonification and ML can be efficiently implemented on low-power edge platforms without any loss of accuracy. The developed platform can be easily expanded to address EEG analysis applications in neonatal and adult population.**

Keywords*—*EEG, AI, CNN, FM/AM sonification, low power, real-time EEG analysis, edge devices, IoT

I. INTRODUCTION

Internet of Things (IoT) technology has a variety of applications in the medical domain, including electroencephalogram (EEG) acquisition and interpretation. A number of EEG acquisition IoT platforms have been reported [1–3]. The acquired data can be sent to the cloud for processing (Figure 1). The development in low power processing capabilities close to the internet edge has led to increasingly complex algorithms to be implemented close to the data source, improving reliability, security, and battery life. Moreover, IoT technology allows older generation EEG acquisition equipment to be connected to the cloud or to other mobile technologies such as tablet PCs. All these features make these devices ideal candidates for improving the quality of care, particularly in under-resourced communities.

Neonatal seizures are common emergencies, and early detection of neonatal seizures is an essential clinical task. Failure to detect such events can lead to lifelong negative outcomes or even death. The main issue is that most neonatal seizures do not present any clinical signs, and those can be diagnosed only by electroencephalography (EEG) monitoring [4]. Video-EEG monitoring and visual interpretation is the gold standard for diagnosis, but it requires years of specialized training, and such expertise is not available 24/7. Many neonatal units in under-resourced communities have only limited or no access to round the clock EEG analysis expertise and equipment. These conditions motivate the efforts directed towards an approach that facilitates the interpretation of brainwaves, increase access to EEG monitoring, lower the cost, and improve the outcome with early detection. The modalities of interpretation aim to assist a healthcare professional in the decision-making process.

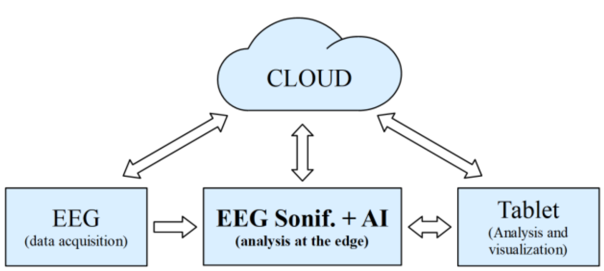

Figure 1. EEG analysis framework.

Significant research on objective methodologies for detecting seizure events using artificial intelligence (AI) has been performed in [5–9]. Most of these techniques are based on explicit feature engineering to capture the frequency, amplitude, energy, temporal structure of EEG [7–8]. While this requires a good knowledge of EEG, the recent advances of deep learning allow this stage to be omitted and still maintain a high degree of accuracy. Recent works have shown that fully convolutional neural networks (CNN) algorithms can be trained to detect neonatal EEG seizures, which match or outperform comparable feature-based machine learning algorithms [10].

Along with AI, which provides an objective assessment of EEG, new methods of subjective EEG analysis have recently emerged in sonification [11–13] to support and complement visual EEG assessment. Employing signal transformation techniques like phase vocoder [14] or frequency/amplitude modulation [15] has demonstrated that sonification in the space of neonatal EEG analysis can lead to improved detection of seizures. These signal processing algorithms are fine-tuned to increase the human ear sensitivity to the presence of seizure-specific pitch and rhythm evolution.

This work implements an EEG analysis framework through AI and sonification on low power IoT edge devices. The analysis includes always-on AI predictions, EEG review mode through sonification with different playback speeds, and intuitive analytics visualization through an LED array. The resulting platform is a versatile, low cost and high accuracy mechanism to support a healthcare professional in the decision-making process.

This research was supported by Science Foundation Ireland Centre for Research Training in Artificial Intelligence under Grant No (18/CRT/6223), and the INSIGHT Centre for Data Analytics.

S. Gomez-Quintana, Grainne Cowhig, Marco Borzacchi, E. Popovici and A. Temko are with Electrical and Electronic Engineering, University College Cork, Ireland, 118227474@umail.ucc.ie (corresponding author), 116304321@umail.ucc.ie, mar.borzacchi@gmail.com, atemko@ucc.ie, e.popovici@ucc.ie,.

A. O'Shea is with Computer Science at Munster Technological University, Ireland, Alison.oshea@cit.ie.

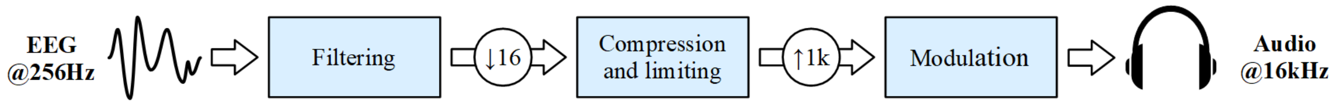

Figure 2. A block diagram for the FM/AM sonification algorithm [15].

II. THE ALGORITHMS

This study implements two algorithms previously developed in the team on a resource-constrained edge device – the neonatal EEG sonification algorithm [15] and the CNN-based seizure detection algorithm [10]. Figure 1 presents a general description of the proposed framework. The implemented algorithms are briefly reviewed next to indicate their suitability for EEG analysis in the resource-constrained device context.

A. *Sonification algorithm*

The FM/AM sonification achieves a waveform-to-spectra mapping as shown in Figure 2:

- Filtering: The EEG signal is filtered between the range of 0.5 to 7.5Hz, with previous subtraction of the DC component.
- Downsampling: The signal is downsampled from 256Hz to 16Hz.
- Compression and limiting: The dynamic range of the signal is reduced using a dynamic-range compressor which utilizes the envelope of the signal in conjunction with two hyperparameters: the threshold (T), which defines a minimum level of the envelope for the compressor to act and the compression ratio (R) which establishes the amount of compression to be applied. The envelope is further utilized in the AM stage.
- Upsampling: The signal is upsampled from 16Hz to 16kHz.
- Modulation: the frequency and amplitude modulations (FM&AM) are performed. The FM utilizes a sinusoidal tone of 500Hz as a carrier signal, which is modulated by the compressed EEG signal using an exponential transformation. The AM utilizes the same envelope used for the dynamic-range compression.

B. *CNN models for automated seizure detection*

A montage with eight channels of EEG is considered for this implementation. For each channel, the EEG signal is pre-processed by filtering with a bandpass filter with a cut-off frequency of 0.5 and 12.8 Hz, and subsequently downsampled to 32Hz. Eight-second windows of EEG (with a stride of 1-second) are fed into the CNN, constructed as a fully connected neural network (FCNN). The usage of convolutions performs feature extraction in a data-driven manner. FCNNs are composed of only convolutional, pooling and activation function layers in order to compute a deep nonlinear filter without the use of resource-heavy densely connected layers. This architecture maintains the translational invariance and hierarchical learning capabilities of a traditional CNN, with a reduced number of learned parameters resulting in a more lightweight model which requires less computational resources at inference time. With no need to implement complex feature extraction routines, this makes the FCNN architecture suitable for edge settings.

The network is applied to pre-processed multi-channel continuous EEG. All filters and pooling operations are only applied across the temporal dimension; temporal ordering is maintained until the final layer when the average across all samples is calculated. All convolutional filters are 3 samples wide with a stride of one sample between successive filtering operations. Every three convolutional layers, there is an average pooling layer that downsamples the data by averaging across four samples with a stride of 3. Each layer has 32 feature maps except the penultimate layer and the final layer which have just two feature maps, one for seizure probabilities and the other for non-seizure probabilities. The architecture is summarized in Figure 3. The resultant model consists of 25k parameters and achieves an AUC performance of 98.5% as reported in [10].

C. *Visualization*

Visual representation of EEG together with CNN inference probabilities for one EEG channel was implemented previously on a tablet PC according to IFCN guidelines [2]. An Android app was also developed in [16] for both visualization and sonification. Visualization through high definition resolution display takes a significant power consumption. For the edge/IoT implementation, power consumption and size of the device are of prime concern. In our scenarios where the CNN is always on, it is important to display key indicators in an intuitive way, including the presence or absence of seizures during a certain period, the number of seizures, the duration of the longest seizure, etc. These indicators can give an early indication for the necessity of further examination of EEG on the tablet. As a result, an 8x8 color LED array was used. The edge device visualization can communicate with the tablet (Bluetooth/WiFi) where the EEG can be further analyzed and evaluated.

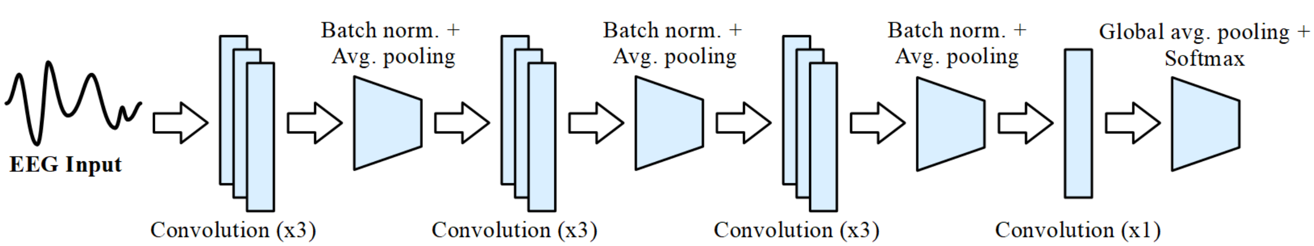

Figure 3. Block diagram of the CNN architecture developed in [10].

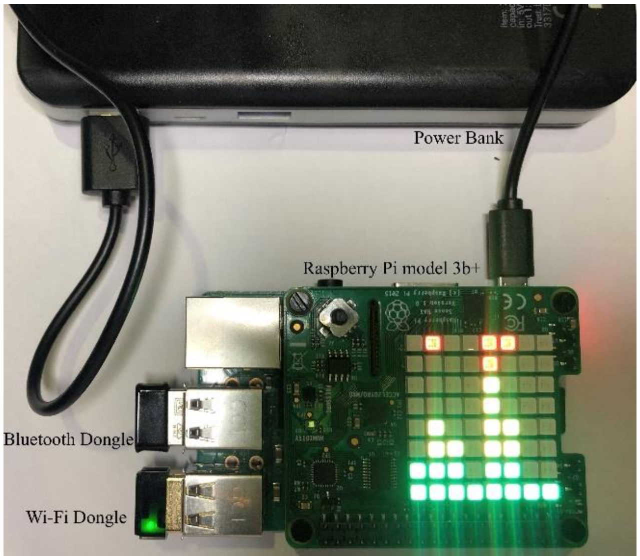

Figure 4. System Realization using Raspberry Pi 3 and LED Array.

III. System implementation results

The presented algorithms are tested using the publicly available EEG data set presented in [17]. The on-board CNN algorithm has previously been tested on this open-access dataset resulting in state-of-the-art performance [10]. The multi-channel dataset contains annotated neonatal EEG waveforms collected at Helsinki University Hospital. This dataset contains EEG segments from 79 full-term babies; signals are sampled at 256 Hz with a 24-bit resolution. The dataset is not composed of long continuous unedited recordings but instead contains 1–2 h excerpts per baby. This overall dataset duration of the recordings is 112h, and the number of seizure events is 342. For this study, all the data are stored on the SD memory card.

A Raspberry Pi 3B+ with a clock frequency of 800MHz was used for the evaluation of the system (Figure 4). The reasons for choosing the platform are connectivity (Ethernet, Wi-Fi, Bluetooth, SPI, USB), processing power, and audio peripherals. The connectivity allows the device to perform as a back-end device to the existing EEG acquisition system (using the USB) as well as connectivity to the cloud (using the Wi-Fi) or to an Android Tablet, as depicted in Figure 1. An 8x8 LED array is also used to reflect the analysis for each of the 8 channels montage. Bluetooth protocol is used for connecting the system to wireless headphones.

The framework presented in Figure 1 allows the coverage of multiple clinical scenarios of operation. Computations in the cloud have the advantage of data aggregation and the potential for more accurate algorithm development for both sonification and machine learning algorithms. On the other hand, cost, accessibility, security and reliability might be of concern, particularly for under-resourced communities, and additional resources or infrastructure have to be allocated to address those. By having the processing close to the source of EEG data, those shortcomings can be overcome.

The envisaged scenario of operation is that the CNN is always on, processing simultaneously 8 channels of EEG. Sonification requires a medical professional, and while the sonification is implemented at the edge, it can be used on-demand, in review mode for various analysis speeds of operation (real-time or fast review with a speed-up factor of 5, 10 or 20). The LED display (Figure 4) can give real-time information through an intuitive color and amplitude mapping per channel. The display can be on-demand with only 2 LEDs continuously active to save power, one indicating if seizures have occurred since the last check and a second LED displaying the instantaneous probability using a color map.

If a seizure has occurred, then the medical professional has an option of review through sonification by listening to the buffered EEG from the SD card or visualizing the EEG together with the CNN inference on a tablet. Although 8 channels are analyzed simultaneously by the CNN inference engine, only one channel is sonified through the review. The selection of the channel for review for sonification is made automatically based on the highest probabilities and duration. The channel selected for sonification is reflected through an LED's lighting on the associated LED array column.

The power performance results of the implementation of the main blocks of the sonification for different review speeds are presented in Table 1. The largest computation time for sonification is for the real-time review for sonification (191ms), while the lowest computation time is for sonification with a review speed of 20 (92ms). The results of the execution time for inference on an 8s EEG window is presented in Table 2. Each inference is preceded by a pre-processing stage, and the total inference time, including the pre-processing, is 50.3 ms for one channel and 402ms for 8 channels.

Table 1: Execution times for FM/AM sonification for a single-channel EEG block of 60 seconds

Review speed	Filterin g (ms)	Downsamp. (ms)	Compr. (ms)	Upsamp. (ms)	Modulation (ms)
(x1)	60.3	11.8	4.47	98.8	396
(x5)	60.1	11.4	4.40	19.7	79.3
(x10)	59.8	11.4	4.45	10.3	40.0
(x20)	58.8	11.1	4.31	5.41	20.0

Table 2: Execution times for CNN inference on a single-channel EEG block of 8 seconds

Convolution (ms)	Batch Norm. (ms)	Averaging (ms)	Soft Max (ms)	Total (ms)
2.23	3.82	1.70	0.07	50.3

Table 3: Energy and execution time measurements over large EEG recordings

	Energy (J)	Exec. time (s)	EEG length (s)
CNN inference			
Performance efficient	5.43	504	6993
Memory efficient	32.5	2806	6976
Sonification (Review speed)			
(x1)	1.36	119	6993
(x5)	0.67	55.1	6993
(x10)	0.36	28.0	6993
(x20)	0.20	14.9	6993

The energy consumption and the execution times for the CNN inference and the sonification of a large EEG block of nearly 2 hours are presented in Table 3.

Two CNN inference implementations are evaluated. One is implemented for performance, with smaller energy consumption and execution times but using high-level python libraries for AI like Keras and TensorFlow. The implementation for lower memory avoids the usage of such high-level libraries at the cost of larger execution times.

Using the sonification with a speed of 20 results in a significant compression ratio of 468 times. This leads to 24h of EEG recording to be reviewed in only 3 minutes. The results of implementation suggest that there is scope to further optimize the always-on CNN inference for both execution time and power consumption. As the inference for 8 channels is taking 402ms (significantly lower than the 1s bound required by the algorithm), this suggests that the core clock frequency can be further reduced by half to 400MHz without a loss in accuracy, also resulting in significant power reduction (50%).

The LED array consumes 630mA when all 64 LEDs are lit. However, the most important information can be represented by only 2 LEDs, with the remaining LEDs being lit only on demand. The two LED show a real-time largest inference probability to color map as well as a history of seizure across any of the 8 channels, respectively. When all array is lit, it gives per channel information (both in terms of the history of seizures as well as real-time probability to color mapping). Further visualization of the 8 channels of EEG can be performed by connecting the proposed system to a tablet or mobile phone on which an app was also developed for further analysis and evaluation. A video demonstration of the inference, sonification and visualization on the proposed system is accessible via https://youtu.be/rco5lqqucJw.

IV. Conclusions

A versatile, energy-efficient system for EEG interpretation was presented. Always-on machine learning inference, EEG review through sonification and intuitive visualization/alert system were implemented on a resource-constrained, low-cost edge device. The system operates as a back-end device to EEG monitoring equipment already available in the hospital setting, accepting EEG data in several formats, including EDF, CSV, etc. The highly versatile system can be connected to the internet (Wi-Fi or Ethernet), or to a tablet for more detailed analysis. Further work will concentrate on further power optimization for both the CNN inference as well as sonification by building customized libraries for the main operations. The implementations will also be expanded to the analysis of EEG across a wider age-group as well as other medical conditions in which EEG analysis can play an important role.

Acknowledgements

The authors would like to thank the University of Helsinki for making the data freely available.

References

[1] R. Martins, et al., "A CMOS IC for portable EEG acquisition systems," *IEEE Trans. Instrum. Meas.,* 47(5), pp. 1191–1196, 1998.

[2] M. O'Sullivan et al., "Neonatal EEG Interpretation and Decision Support Framework for Mobile Platforms," *in Proc. 40th EMBC*, pp. 4881–4884, 2018.

[3] N. Verma, et al., "A Micro-Power EEG Acquisition SoC With Integrated Feature Extraction Processor for a Chronic Seizure Detection System," *IEEE J. Solid-State Circuits*, 45(4), pp. 804–816, 2010.

[4] D. M. Murray, et al., "Defining the gap between electrographic seizure burden, clinical expression and staff recognition of neonatal seizures," *Arch. of Dis. Child. Fetal Neonatal Ed.*, 93(3), pp. F187–F191, 2008.

[5] S. R. Mathieson et al., "Validation of an automated seizure detection algorithm for term neonates," *Clin. Neurophysiol.*, 127(1), pp. 156–168, 2016.

[6] E. M. Thomas, et al., "Discriminative and generative classification techniques applied to automated neonatal seizure detection," *IEEE J. Biomed. Health*, 17(2), pp. 297–304, 2013.

[7] A. Temko, et al., "EEG Signal Description with Spectral-Envelope-Based Speech Recognition Features for Detection of Neonatal Seizures," *IEEE Trans. Inf. Technol. B.*, 15(6), pp. 839–847, 2011.

[8] A. Temko, et al., "EEG-based neonatal seizure detection with Support Vector Machines," *Clin. Neurophysiol.*, 122(3), pp. 464–473, 2011.

[9] N. J. Stevenson, et al., "An Automated System for Grading EEG Abnormality in Term Neonates with Hypoxic-Ischaemic Encephalopathy," *Ann. Biomed. Eng.*, 41 no. 4 pp. 775–785, 2013.

[10] A. O'Shea, et al., "Neonatal seizure detection from raw multi-channel EEG using a fully convolutional architecture," *Neural Netw.*, 123, pp. 12–25, 2020.

[11] T. Väljamäe, et al., "A review of real-time EEG sonification research," *in Proc. 40th ICAD*, pp. 6–10, 2013.

[12] H. Khamis, et al., "Detection of temporal lobe seizures and identification of lateralization from audified EEG," *Clin. Neurophysiol.*, 123(9), pp. 1714–1720, 2012.

[13] J-W Lin, et al., "Visualization and sonification of long-term epilepsy electroencephalogram monitoring," *J. Med. Biol. Eng.*, pp 1–10. 2018.

[14] J. Flanagan and R. Golden, "Phase Vocoder," *IEEE J. Bell Syst. Tech.*, Minneapolis, 1966.

[15] Gomez et al., "On sound based interpretation of neonatal EEG," *in Proc. 29th ISSC*, pp. 1–6, 2018.

[16] J. Poveda, et al., "Portable neonatal EEG monitoring and sonification on an Android device," *in Proc. 39th EMBC*, pp. 2018–2021, 2017.

[17] N. J. Stevenson, et al., "A dataset of neonatal EEG recordings with seizure annotations," *Scientific Data*, 6(1), pp. 1–8, 2019.