Portable Neonatal EEG Monitoring and Sonification on an Android Device

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***Abstract*— Clinical evaluation of electroencephalogram (EEG) is important for understanding and monitoring the electrical activity present in the brain. In collusion with engineering advances, the movement towards portable, rapid and low-cost EEG monitoring is growing. This will allow a greater availability of monitoring technologies for assessing brain function and health in disadvantaged communities. This paper presents an alternative method for interpreting neonatal brain health in real-time via the sonification of EEG on a smartphone. The paper discusses the implementation of the real-time EEG sonification using a phase vocoder and shows how the method is achievable using low-cost smartphone technologies with energy efficient algorithms.**

I. Introduction

Neonatal brain injuries are a serious concern for clinicians and parents worldwide [1]. The only method to accurately detect all neonatal brain injuries is continuous multi-channel EEG monitoring. Interpretation of neonatal EEG requires a neurophysiologist with specific expertise in neonatal EEG. This expertise is not available on a 24h basis, 7 days a week. To fill the gap in the availability of appropriate expertise, clinical staff in the NICU are using a simpler form of EEG monitoring called amplitude integrated EEG, or aEEG [2]. Numerous studies have since shown that aEEG has very limited usefulness in detecting abnormal neonatal brain function and have questioned its appropriateness for use in the neonatal population in general [3]. The demand for an alternative method to monitor the brain health of neonates is increasing. The human hearing input is better than the visual input with regard to assessing both the spatial and temporal evolution of the frequency characteristics of a signal [4]. Hearing is flexible and low-cost. It allows for faster processing than visual presentation and releases visual sense for other tasks [5], [6].

Current EEG acquisition and visualisation systems cost thousands of euros. Implementing a smartphone-based system in collaboration with a portable acquisition device solves the issues of cost, portability and rapid assessment. Android technology is widely available across the globe. As of 2015, 37% of the population in developing nations own a smartphone [7].

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Figure 1. Neonatal Brain Stethoscope: EEG Sonification and Monitoring using Android Device.

This paper forms the back-end of a new emerging product, the Neonatal Brain Stethoscope as illustrated in Fig. 1. The device receives the EEG signal via Bluetooth from the EEG acquisition board, and is capable of real-time sonification and visualisation of EEG on an Android device. This work adapts the previously designed offline Matlab algorithm [5] to perform in real-time and sonify a single channel of EEG on an Android device. Thus, the algorithm can be used with Bluetooth enabled portable EEG acquisition devices such as OpenBCI, g.MOBIlab+ or Cognionics portable data acquisition systems.

II. Neonatal EEG Sonification

A. Communication

The communication between the EEG acquisition system (in our case an EEG database) and the smartphone is completed using Bluetooth Low Energy (BLE). BLE is preferred over WiFi and USB in this case. The benefits of using wireless connection over wired connection are the usability and reduction of errors and artefacts due to wire movements. Compared to WiFi, BLE has lower power consumption which simplifies the design of both the front-end and backend of the project [8]. BLE is capable of transfer speeds up to 276 kbps, which is more than sufficient for this application. In addition, using BLE means that the WiFi embedded chip in the smartphone can be used for other purposes. For example, real-time data can be uploaded to the cloud where various algorithms or medical personnel can further assess the EEG, allowing for improved connectivity in the context of Internet of People framework.

B. Processing using Phase Vocoder

A Phase Vocoder is an analysis-synthesis method used for scaling the frequency range [9]. The Phase Vocoder preserves the spectral characteristics and does not affect the time duration, which allows for its usage for real-time signals

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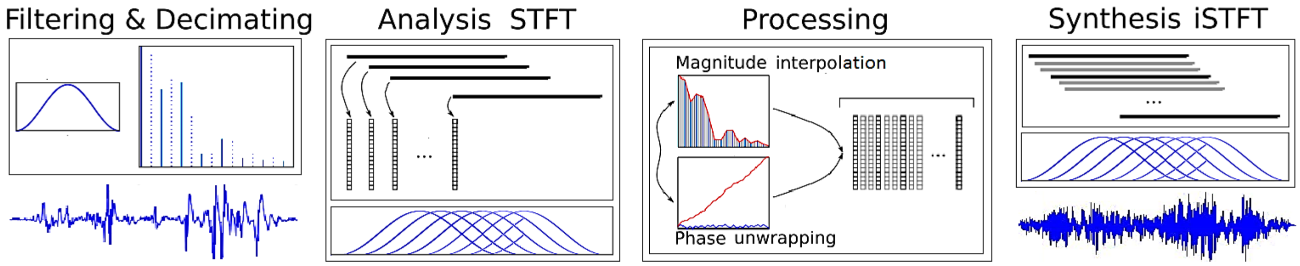

Figure 2. Neonatal EEG Sonification using phase vocoder

such as EEG. The most prominent frequencies in neonatal EEG were mapped to the frequency range of human screaming using the phase vocoder. The seizure detection performance reported was better than using conventional aEEG [6]. The signal flow can be described in four main steps: pre-processing, analysis, processing, and synthesis as seen in Fig. 2. The last three are related to the phase vocoder. The EEG was transmitted at a rate of 250 Hz to the phone.

Pre-processing: The frequency range of interest in neonatal EEG is from 0.5-13 Hz. The raw signal is low-pass and high-pass filtered and down-sampled to 32Hz.

Analysis: Discrete Fourier Transform (DFT) with a size of 32 samples (1s) is applied to the signal. The window hop size is 4 samples. The obtained STFTs are decomposed into magnitude and phase. Each of the signals (magnitude and phase) can be seen as a matrix, whereby each point corresponds to a frame in time and a DFT bin in frequency.

Processing: The magnitude of the signal is linearly-interpolated by a factor of 500 in order for the EEG to be reproduced at a 16 kHz sampling rate. The phase is measured modulo 2π and it is un-warped to keep track of the cumulative phase variation in order to preserve the phase consistency as seen in the formulae below.

$$Pe(i) = 2\pi \; hop \; \frac{i}{N} \tag{1}$$

$$\delta P^i[k] = \left(P_k^i - P_{k+1}^i - P_e^i\right)(mod 2\pi) - \pi \tag{2}$$

$$P_a^i[k] = P_a^i[k-1] + \delta P^i[k] + P_e^i \tag{3}$$

where (1) is the expected phase advance for a given i-band, (2) and (3) are the deviation of the phase advance and the cumulated phase in the k-frame for a given i-band, respectively. P_k^i is the extracted phase in the k-frame for the i-band.

It can be seen from Eq. 1 – 3 that this process can be implemented using multiple threads. In fact, Eq. 1 can be pre-computed as it only depends on the band and the selected hop size. The required information for computing is only contingent on the actual band. Therefore, each band can be processed separately, enabling multi-threading. The interpolation of the magnitude can be implemented in a similar manner.

Synthesis: An inverse DFT (iDFT) and an overlap-add (OLA) is applied using the same window as in the analysis section. The output after synthesis is a 16kHz signal which is essentially the unformatted audio signal.

C. Core Parameters

There are mainly three parameters that change the properties of the audio generated by the Phase Vocoder, namely: the rate, the window size and the hop size. The rate affects the frequency scaling as discussed below. A value of 500 was chosen to scale the frequency range of 0.5-12.8 Hz to 250-6400 Hz. There are various reasons for this choice. Firstly, the dominant frequencies of neonatal EEG seizures are in the range of 0.5-6 Hz [5], which is mapped to 250-3000 Hz, where the human ear has high level of sensitivity [10]. Although the highest ear sensitivity is in the range of 1000-4000 Hz approximately, the effects of Presbyacusis are proportional to the frequency [11]. For that reason, the seizures are mapped to the lower boundary of this range to ensure all medical personnel have equal capacity. Lastly, upon testing, it was noted that using this scaling factor results in the seizures being perceived as similar to a human screaming, which gives a sense of alarm and urgency. The window and DFT size was set to 32 samples which is the lowest power of two which can use an optimized FFT. Also, increasing this size resulted in a more complex and chaotic sound which made differentiating between brain injuries more difficult. The hop size affects the duration of the perceived 'notes'. This parameter was set to 4 samples, which corresponds to an eighth of a second. This results in an overlap of 87.5%, which ensures a smooth sound and heightened time precision. Increasing this value warps the perceived sound to a succession on long notes, decreasing this value culminates in a more 'staccato' type sound.

III. Android Implementation & Methodology

A. Implementation

The backend of the application was designed using the Pipes and Filters design pattern as shown in Fig. 3. Various threads are able to perform part of the processing and send the result to the next thread, as a pipeline. The Multiple Program Multiple Data (MPMD) model was implemented. In order to allow a communication between threads, an object called Pipe, which solves the producer-consumer problem using a First-Input-First-Output (FIFO) buffer with blocking accessing methods, is implemented. A Job is an entity that contains one band and some related parameters used in the processing of the former. A Worker is an entity in charge of processing one Job at a time. The four general threads are classes extending Runnable. Their functions are outlined below.

CaptureRunnable: Establishes and manages the Bluetooth connection, including capturing the packets, unpacking the data, reconstructing the raw EEG data and sending the raw EEG data via a Pipe.

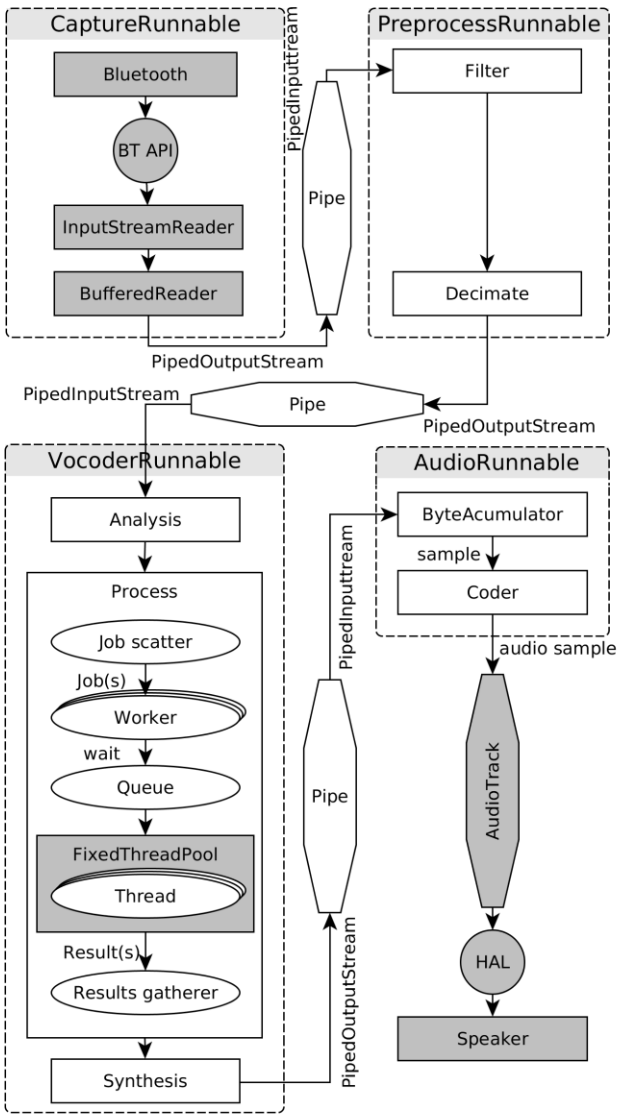

Figure 3. The flowchart of Android-based EEG Sonification

PreprocessRunnable: Implements the bandpass filter and signal decimation. It uses a Pipe to send the data for further processing. This is completed in a separate thread as some of the portable EEG acquisition boards incorporate internal pre-processing. Thus, the thread can easily be bypassed if the board applies filtering before transmitting the signal.

VocoderRunnable: Scales the bandwidth of the EEG to an audible band. As seen in Fig. 3, the analysed EEG is split into bands, multiple jobs are created and distributed to workers. These workers are waiting in a queue with a fixed number of threads associated. Lastly, the results of all the workers are gathered and the synthesis is completed.

AudioRunnable: Adapts the format of the current samples into a compatible format which can be processed by the Android device. The following formats have been implemented in this study, PCM 32-bit IEEE single precision float, PCM 16-bit and PCM 8-bit, depending on the API version of the Android device.

B. Multi-threaded Vocoder

Using the method outlined above, the application was unable to run in real-time on the tested device. The VocoderRunnable thread, used an entire core, creating a bottleneck in the processing chain. For this reason, a fixed pool of threads was built by implementing the Single Program Multiple Data (SPMD) model, for the vocoder. The distribution of the threads to various cores cannot be decided by the application itself. However, splitting the vocoder's workload into more than one thread allows the operating system (OS) to have oversight on the distribution of cores. This method should implement the threads in the most efficient manner depending on the device, power configuration, and API version.

IV. Results & Discussion

The following results were obtained using a Samsung Galaxy Grand Prime which has 4 ARM Cortex-A52 cores at 1.25 GHz with 1 GB of RAM, running Android 5.1. The EEG data used throughout this test was obtained from the CHB-MIT Scalp EEG Database [12]. The data was buffered and fed into the sonification pipeline at 250 samples per second, similar to the manner in which the previously mentioned portable EEG acquisition devices transmit data. The lithium ion battery used in the device has a capacity of 2600 milli-Ampere-hours (mAh). The tests were run on the isolated vocoder thread to allow for direct analysis of the sonification algorithm. The vocoder input buffer was filled and the test is run for a 1 minute period. The test parameters are defined below.

Pool Size: Number of Workers/Threads allowed to be run in parallel simultaneously in the vocoder.

Number of Frames: Number of DFT frames used as an input for the Processing block. This substitute the number of elements to interpolate at once by each job.

CPU-user: Percentage of CPU time of the application in user mode, which is the non-privileged use of the device.

RAM: Number of megabytes allocated in the Random Access Memory (RAM) of the device on average.

Power Consumption: milli-ampere hours (mAh) used by the application.

Real-Time Factor: Parameter related to the speed of the application referenced to real-time. A factor less than 1.00 denotes that the real-time capacity is achieved and exceeded.

Table I shows the results of the performed tests. The power consumption of the phone without the app running is 22 mAh on average (the majority of which is consumed by lighting the display). The average power consumption values over the 5 minute test of the app running 1, 4, 8 and 17 threads are 13.1 mAh, 11.15 mAh, 11.3 mAh and 10.425 mAh respectively. To put this into perspective, running the Facebook app for the same 5 minute period, on the same phone, consumes 15.8 mAh. Facebook consumes 34% more power than the designed phase-vocoder based EEG sonification running on 17 threads.

Additional parameters not shown in Table I include the CPU-kernel, which is the percentage of CPU time for application running in kernel mode (with unrestricted access to underlying resources of the smartphone, e.g. I/O operations, transferring data from or to RAM or peripheries).

TABLE I. MULTI-THREADED VOCODER RESULTS

Pool Size	Num. Frames	CPU-u (%)	RAM (MB)	Power (mAh)	Real-time
1	2	34±02	09±02	13.4	0.96
1	9	37±05	14±04	13.2	0.97
1	17	36±07	16±04	13.4	0.99
1	65	36±11	34±05	12.4	0.95
4	2	39±02	08±02	12.7	0.88
4	9	39±11	15±04	11.0	0.79
4	17	40±09	20±06	10.7	0.79
4	65	40±26	46±16	10.2	0.77
8	2	39±03	09±02	12.9	0.89
8	9	39±04	14±04	11.1	0.79
8	17	40±11	20±07	10.7	0.78
8	65	46±24	40±10	10.5	0.79
17	2	38±04	10±03	10.1	0.77
17	9	40±13	14±06	10.9	0.78
17	17	39±12	23±09	10.6	0.77
17	65	43±15	46±14	10.1	0.77

The CPU-kernel value is less than 10% in all cases. From Table I, it is obvious that utilising multiple threads results in much quicker and more efficient execution of the vocoder as it allows Android to distribute the tasks effectively.

Using multiple threads and increasing the number of frames to be interpolated at once, results in an increase in CPU-u. Counterintuitively, this is actually desirable, as the more CPU-u, the greater the allowance to spread the tasks, thus allowing full use of the 4 cores of the processor. Increasing the number of frames and the number of threads running simultaneously causes an increase of RAM allocation. The pool size and number of frames is limited to 17 and 65 respectively. This is due to the DFT size (32), which results in 17 audio bands. As the job is split by audio bands, it would be excessive and unnecessary to have more threads as they will be sleeping. Interpolating more frames simultaneously results in greater latency as the app would have to wait until the buffer is filled before processing the data and finally listening to the data. 65 frames corresponds to roughly 2 seconds at 32Hz sampling rate. Thus, 2 seconds is the lowest achievable latency. Increasing the number of frames will further decrease the real-time feel. As discussed previously, using more threads reduces the power consumption. Power consumption is closely related to the real-time factor: adding more threads, results in a quicker execution of the vocoder task. A snapshot of the application is illustrated in Fig. 4. A video demonstration is accessible via: https://youtu.be/MXLUVKwPX6M

V. CONCLUSION

The feasibility of obtaining real-time analysis, pre-processing, processing and synthesis of EEG using a low-cost Android device is demonstrated. Furthermore, the study has provided valid insights into the optimisation of the processes and data flow involved. It can be concluded that splitting the workload of the vocoder and increasing the number of threads to be equal to the number of frequency bands increases the real-time capacity and reduces the power consumption. Furthermore, depending on the capabilities of the Android device, the buffer size (number of frames) can be increased to aid the real-time factor and energy efficiency, although this directly results in a greater lag time.

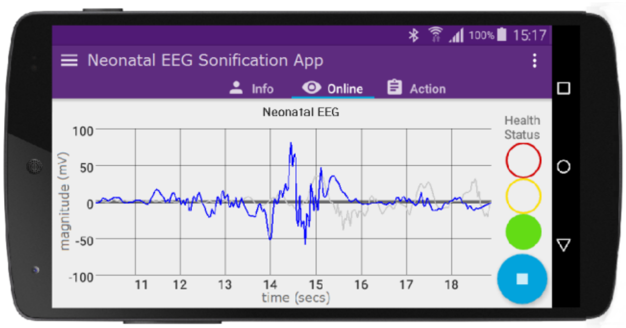

Figure 4. The Android app demo.

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