Edge-based Real-time Fetal Electrocardiography Monitoring in the Home Setting

Floranne Tavailau Ellington[1], Berken Demirel[1], Daniel Jilani[1], Mohammad Abdullah Al Faruque[1], Hung Cao[1]

[1] Department of Electrical Engineering and Computer Science, University of California, Irvine, Irvine, USA

Abstract

Health monitoring is increasingly moving to continuous, home-based applications with real time analytics. Fetal monitoring has been traditionally carried out in the hospital during checkups. While newly developed wearable systems offer home monitoring capabilities, rigorous real-time analytics require mobile or cloud connections for complex computation. However, these architectures result in higher energy output from the sensors and devices, reliance on a steady Bluetooth or WiFi signal, potential latency and synchronization variables, and data privacy issues. Furthermore, it is impossible to achieve telemedicine in resource-poor locations where mobile phone and internet are not accessible. To address these problems, we develop an edge computing paradigm for future integration in a compact abdominal patch to monitor the fetus remotely in the home. The energy saving and cost-effective algorithm, namely Lullaby, was developed to extract the fetal heartrate from a pregnant mother's abdominal electrocardiography (ECG) signal. The algorithm was validated using the Physionet 2013 Challenge Dataset and achieved an average F1-score of 81%. Our experiments have shown that the proposed approach is deployable in a multitude of physical systems, either as a standalone fetal ECG monitoring patch or integrated into a more complex architecture. Additionally, evaluation on real hardware shows that proposed algorithm is suitable for devices having a minimum RAM of 64KB, which can be implemented on low-cost MCUs and designed to be energy saving for longer, continuous monitoring.

1. Introduction

Edge computing has emerged as a new approach for compiling algorithms for the Internet of Things systems. This approach versus its alternative architecture schemes, fog or cloud computing, where both models rely on outside, connected devices for partial or full processing, has

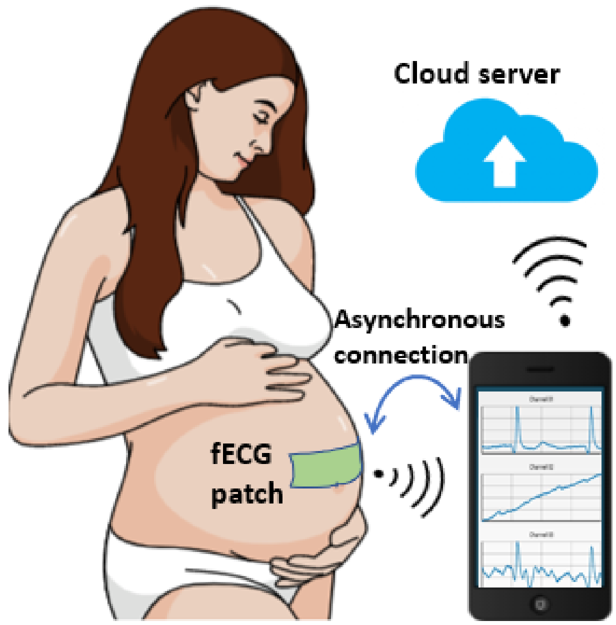

Figure 1. Fetal ECG Patch Edge System with optional FOG/Cloud configuration for storage and display.

the computation fully performed on the edge device, giving this method its name. This has advantages for a plethora of applications and fields as it eliminates the transfer delay from the edge to the central processing unit, has less privacy issues from data transmission, saves energy from constant broadcast of raw data, and does not require a consistent Bluetooth or WiFi connection to a paired device or the cloud while providing continuous and low-energy monitoring [1]. As such, this opens possibilities for more independent and convenient devices, shorter and quality signal processing algorithms, and smarter and more secure transmission techniques. This allows for other focuses for the device construction such as low memory and energy optimizations for continuous use and lower construction costs.

Strides have been made lately in sensing technology and signal processing to enhance the signal-to-noise ratio (SNR) of home-based electrocardiogram (ECG) signals to make them comparable to clinical counterparts. Nevertheless, acquisition and analysis of fetal ECG/heart rate (fECG/fHR) are still immature. Efforts have been made to compose systems with wireless devices to record and send data to a peripheral smartphone for fHR extraction [2]–[4]; nevertheless, these architecture schemes still require a steady and synchronized connection to a fog device for continuous extraction, cost more energy to transmit for the systems, and needs the user to be using a paired smartphone. Additionally, these and other existing approach do not take advantage of edge computation abilities. As projected by Moore's Law, MCUs have evolved exponentially, allowing for complex neural networks to compile on them in a timely manner [5], [6] and causing less sophisticated processors become more common and cheaper to manufacture. In this context, there is a clear demand for cost-effective, energy-saving, and user-friendly systems providing non-invasive, continuous fHR monitoring in daily life.

In this paper, we propose a novel, fast, and light fHR detection algorithm adapted from [7] running on the EFM32 Giant Gecko ARM Cortex-M3-based 32-bit MCU using low energy and a low memory footprint and is validated using the Physionet 2013 Challenge Dataset. The algorithm models the fECG as a periodic signal and uses an approximated periodic trend as a feature to detect fetal heartbeats. Aside from this, the algorithm mostly uses simple matrix manipulations and peak finding algorithms to perform a fast and simple detection for fetal heartbeats. This system will be integrated into an abdominal patch for future clinical trials with the University of California, Irvine Medical School.

2. Related Works

The gold standard for monitoring fHR is the fetal scalp electrode (FSE), which is an invasive ECG device that is attached directly to the scalp of the fetus. Although the ECG is taken directly from the fetus, there is an increased risk of complication due to the procedure [8], [9]. Two non-invasive fHR detection methods exist, ultrasound and abdominal ECG (aECG), where the latter of the two was found to be more comparable to the FSE [10]. It is more difficult to detect fHR and fHRV in aECG than FSE because of significant contaminating noises such as the maternal ECG (mECG) but much more feasible to implement into a mobile system.

Several prototypes of mobile fHR monitoring system which can accommodate daily life have been proposed in recent years. Sarafan et al. presented a system which uses a fetal patch to record aECG data which is then sent to the cloud for real-time fHR processing through an android phone hub device [2]. Boatin et al. designed a wireless monitoring system using ultrasound to detect fHR and received overall positive feedback from pregnant subjects and clinicians [3]. Yuan et al. utilized a fast version of the independent component analysis algorithm (FastICA) [11] to create an aECG system that directly computed fHR on an android smartphone [4].

Most real-time systems for fHR detection are reliant upon the cloud to support computationally heavy denoising algorithms. Popular aECG denoising algorithms include the extended Kalman Filter, Template Subtraction, and Independent Component Analysis [12], all of which are very computationally intensive. Running these algorithms on a small device such as a phone would be difficult due to computational limitations. However, cloud computing can become expensive if under constant use and dependent upon a reliable WiFi connection. The use of FastICA on an Android smartphone by Yuan et al. is a significant deviation from the mainstream. The authors instead chose to use the DaISy (Database for the Identification of Systems) database for the validation of their system which uses an unimpressive 250Hz sampling rate [4]. A sampling rate of 1kHz is the current gold standard for aECG data as offered by Physionet.

Edge healthcare applications are a highly explored area in recent years, but it has been focused in areas regarding patient information management [1], [5], [13], [14] and vital recording [6], [15] rather than for maternal and fetal healthcare. These methods provide a glimpse of the advantages of continuous and remote monitoring, but the projects into this domain of research have focused on patients' self reporting or HR and steps, which are relatively computationally simple compared to extracting fHR.

For fetal extraction on the edge, only one was reported, in which the authors implemented a remote fetal monitoring system using an Arduino board to receive and calculate the fHR in real-time using data from the connected ECG and PPG sensors before transmitting the final data [16]. However, it was only a preliminary study using edge-based technology and needs to be built upon with more research dedicated to this topic.

3. Methodology

In this work, the Lullaby algorithm is evaluated on the Physionet 2013 challenge database set A, which contains 75 one-minute abdominal ECG recordings sampled at 1000 Hz. For this paper, only the original first 25 datasets will be used. The data also includes annotations of the fetal ECG taken from a direct scalp electrode.

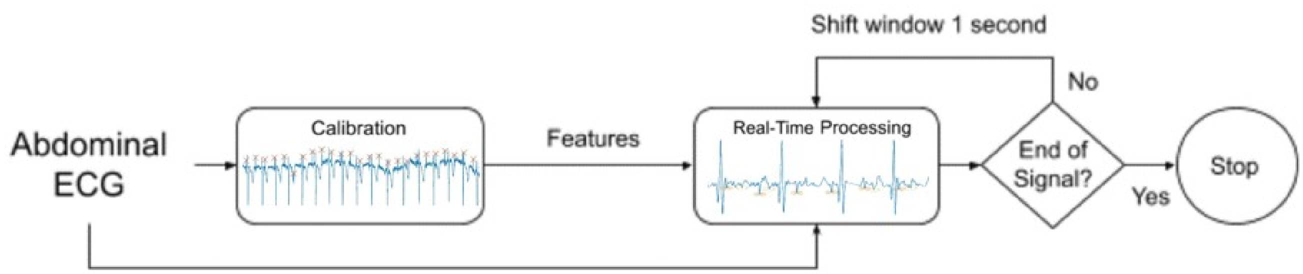

Figure 2. FECG Extraction Algorithm Overview.

3.1. The Lullaby Algorithm

The algorithm is separated into two main parts: the 12 second calibration window and the real-time processing which continues until the signal is finished. In the calibration phase, the first 12 seconds of the abdominal ECG are used to determine the features of the fetal peaks to selectively choose candidate peaks in the real-time processing phase. In the real-time processing phase, the abdominal ECG is segmented into 4 second windows and processed to determine the position of fetal peaks throughout the entire window. However, only the fetal peaks positions in the last 1 second of the 4 second window are outputted. The window then shifts forward in time 1 second and the process repeats until the end of the abdominal ECG is reached (Fig. 2). The original algorithm was written in MATLAB and then converted to C code using the compiler provided through MathWorks Inc.

3.2. The Microcontroller and Simulation

We evaluate our proposed method memory footprint and energy consumption on the EFM32 Giant Gecko ARM Cortex-M3-based 32-bit microcontrollers (MCUs), which has a 1024 KB flash memory and 128 KB of RAM with a CPU speeds up to 48 MHz. The algorithm is then simulated on the microcontroller with the data extracted from the Physionet 2013 challenge database set A and run multiple times to determine the memory usage, execution time, and energy consumption with the chosen board.

4. Results

Table 1 shows the execution time, energy consumption, and required memory for each operation that runs on the device. The operations are implemented and deployed to the target device using MATLAB (MATLAB and Coder Toolbox Release R2020b, The MathWorks, Inc, USA).

The overall execution time for a 12-second fECG segment takes 1200 ms in the device with 580.2 μJ energy consumption. As the *Calibration* phase includes more samples compared to *real-time*, its computational overhead dominates the overall operations. Also, our proposed method is compatible with any device with a minimum RAM of 64 KB. As a result, our method guarantees high performance while maintaining the edge devices' requirements.

Table 1. Memory Footprint, Execution Time and Energy Consumption Evaluation on EFM32 Giant Gecko Development Board.

Operations	Exe. Time (ms)	Avg. Energy (μJ)	Flash Memory Footprint (KB)	RAM Memory Footprint (KB)
Calibration Phase	1200	580.2	9.4	20.7
Real-time Phase	49.24	2.27	44.4	29.3
Overall	—	—	$\geq$ 64 KB	$\geq$ 32 KB

5. Discussion and Conclusions

From the simulations using the EFM32 MCU, we were able to determine the Lullaby algorithm's potential for real-time processing on the edge. With a minimum delay due to the calibration phase reading the first 12 seconds and processing in 1.2 seconds, the continuous monitoring calculations afterwards is able to run smoothly and accurately at almost 0.05 seconds on the MCU. Alongside this fast performance, the memory usage is compatible with a minimum of 32KB of RAM and 64KB of flash memory on a device, making it more feasible for MCU and thus wearable adaptation. Most smart watches utilize MB or GB of RAM and GB of flash memory in comparison. Alongside the memory usage calculated, the algorithm runs with an average of 580.2 μJ for calibration and 2.27 μJ for the real-time processing afterwards. For one user in one session, this configuration can continuously record multiple days or weeks given a decent battery source and provide data of the fetus during the mother's daily activities, which can reveal more about their condition and the impacts of daily life on perinatal development.

The algorithm is able to determine the fetal peaks with an average F1 score of 81% despite the limited computational resources available, making remote reporting of the fetal HR possible using this configuration. As the Lullaby algorithm can also detect other features of the ECG signal, this approach may be expanded in the future to detect early signs of heart abnormalities in the developing fetus outside of hospital visits.

In conclusion, this work explores the viability of the simple-yet-novel Lullaby algorithm on an edge platform and thus, enables a new avenue of remote fetal healthcare. Using edge computing with fetal development has been underutilized in the past despite the clear advantages of having continuous, non-invasive monitoring. As this project demonstrated the clear use of acquiring fHR using a low memory platform and low energy algorithm, the possibilities of expanding this system to detect other features of the fetal ECG signal as well as incorporating other sensors for perinatal health monitoring is endless with the projection of hardware advances.

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Address for correspondence:

Hung Cao
4406 Engineering Hall
University of California, Irvine
Irvine, CA 92697