Evaluation of feature extraction techniques for an Internet of Things Electroencephalogram

Evaluación de Técnicas para la extracción de características en un electroencefalograma del Internet de las Cosas

David Barahona-Pereira[1]

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1 Ingeniero en Electrónica egresado de la carrera de Electrónica del Instituto Tecnológico de Costa Rica. Correo Electrónico: davidbp.13@gmail.com

Palabras clave

IoT; EEG; extracción de características; FIR, método de Welch; DWT.

Resumen

El creciente paradigma del Internet de las Cosas (IoT) está revolucionando nuestra vida con la introducción de nuevos servicios y la mejora de aplicaciones existentes. IoT cubre un creciente número de aplicaciones en diferentes áreas incluyendo el cuidado de la salud. Una aplicación específica en el cuidado de la salud es el monitoreo de la actividad eléctrica en el cerebro utilizando electroencefalogramas (EEG) con dispositivos de IoT portables. Debido a restricciones de portabilidad y tamaño, la mayoría de los dispositivos de IoT son alimentados con baterías lo que implica una implementación energéticamente eficiente en hardware y software en conjunto a un uso eficiente de los recursos normalmente limitados.

Este trabajo evalúa tres diferentes técnicas de extracción de características para un IoT EEG en términos de tiempo de ejecución, consumo de memoria y potencia. Las técnicas estudiadas fueron exploradas y simuladas llevando a la escogencia de FIR, el método de Welch y DWT para evaluación. Las técnicas se implementaron en una plataforma MSP432P401R Launchpad, en donde un procedimiento de evaluación se desarrolló para verificar el desempeño de los códigos. Las implementaciones fueron validadas contra referencias simuladas y optimizadas para velocidad, tamaño de código y consumo de potencia. El resultado de la evaluación realizada provee una comparación valiosa entre técnicas que puede ayudar a cualquier diseñador en la escogencia de la técnica adecuada basado en objetivos de diseño y restricciones de recursos.

Keywords

IoT; EEG; feature extraction; FIR, Welch's method; DWT.

Abstract

The emerging paradigm of Internet of Things (IoT) is revolutionizing our life with the introduction of new services and the improvement of existing applications. IoT is covering an ever-increasing number of applications in different domains including healthcare. One specific application in personal healthcare is the monitoring of the electrical activity in the brain using Electroencephalogram (EEG) with portable IoT devices. Due to portability and size constraints, most IoT devices are battery-powered which calls for an energy-efficient implementation in both hardware and software along with an efficient use of the often limited resources.

This work evaluates three different feature extraction techniques for an IoT EEG in terms of execution time, memory usage and power consumption. The techniques under study were explored and simulated leading to select FIR, Welch's method and DWT as the ones to be evaluated. The techniques were implemented on a MSP432P401R LaunchPad platform, where an evaluation procedure was developed to assess the code performance. The implementations were validated against simulated references and also optimized for speed, code size and power consumption. The result of the performed evaluation provides a valuable comparison between the techniques which can help any designer in choosing the right technique based on design objectives and resource constraints.

Introduction

This project was developed as part of the current research in wearable healthcare monitoring systems by the Internet of Things for Healthcare group of the Chair for Embedded Systems (CES) at the Karlsruhe Institute of Technology (KIT) in Germany. An electroencephalogram (EEG) is a device that is able to measure and record the electrical activity of the brain. EEG is commonly found in medical applications, however its use has been extended to other fields such as Brain Computer Interfaces (BCIs) in tasks like controlling a robotic arm by imagining hand movements [7]. An IoT EEG is intended to be a portable and hence battery-powered device, therefore it is important to find the best way to face inherent challenges in computation capability and energy capacity. One important stage in the operation of an EEG is feature extraction, this stage uses several signal processing techniques to get relevant information about the brain activity usually by measuring power in different frequency bands. Since there are many techniques that can be used in feature extraction, it is important to compare them in order to develop a criteria about which can be better suited to face the previously mentioned challenges. This work evaluates different feature extraction techniques from perspectives such as execution time, memory usage and power consumption in a microcontroller platform.

Materials and Methodology

In order to evaluate the feature extraction techniques, the process depicted in figure 1 can be followed. The first stage of the process involves an extensive investigation about which are the most relevant techniques for feature extraction, as well as their characteristics and possible optimization schemes. Then, the simulation stage uses the findings of the previous investigation to explore how each of the techniques under study behaves in the presence of a real EEG signal and also to provide a reference to validate the implementations. In the platform setup stage, the goal is to find a procedure to measure the parameters that will be evaluated. The implementation stage is the core of the solution and it consists in implementing each selected technique in the microcontroller platform. Here, the correct behavior of each technique needs to be validated and also since the main approach is to face computation and power challenges, possible optimizations must be carried out as well. In the final stage, execution time, power consumption and memory usage are measured and the results are used to compare each technique in order to evaluate how they fit in the final design of the device.

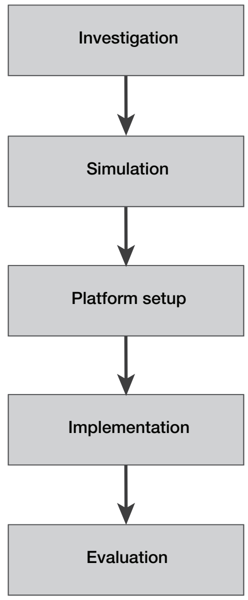

Figure 1. Stages of the project.

Feature Extraction Techniques in EEG

An EEG is a test device used to evaluate the electrical activity in the brain. Since brain cells communicate with each other through electrical impulses, EEG can be used to detect potential problems associated with this activity. The test is typically noninvasive, it tracks and records brain wave patterns through a set of electrodes attached to the scalp with wires. Measurements taken from an EEG consist of an electrical wave that varies in time, much like a sound signal or a vibration. As such, it contains frequency components that can be measured and then analyzed, these frequency components have interesting and valuable properties. As shown in table 1, brain waves have been categorized according with their frequency range into four basic groups known as: Delta, Theta, Alpha and Beta.

Table 1. Cognitive states related to EEG frequency bands

Band	Frequency range (Hz)	Brain activity
Delta	0.5 - 4	Deepest meditation and dreamless sleep
Theta	4 - 8	Light sleep
Alpha	8 - 13	Relaxation
Beta	13+	Consciousness

There are several techniques that can be addressed for feature extraction in EEG. After an exhaustive investigation and several simulations FIR (Finite Impulse Response) filters, Welch's Method and DWT (Discrete Wavelet Transform) were selected as the techniques to be evaluated.

FIR filters are digital filters that have no feedback so their impulse response is of finite duration because it settles to 0 after some time [10]. For an FIR filter of order N, the output sequence consists of a weighted sum of past input values. They are used in applications in which phase characteristics are very important, they are always stable and show a linear phase response. They exhibit a delay that could be critical in certain applications and also they usually have a high order since they use a lot of inputs to calculate the output. This is a time domain analysis that is able to provide a representation of power over time for each band separately.

Welch's method is a technique based on Fourier analysis which states that every signal can be represented or approximated by sums of trigonometric functions [6]. This method attains to calculate Power Spectral Density (PSD) that refers to the spectral energy distribution that would be found per unit frequency in a signal. Welch's method is based on the use of overlapping windows to the signal in which a periodogram is calculated for each window and then those periodograms are averaged between them to compute PSD [2]. This is a frequency domain analysis that is able to provide a representation of power over different frequency ranges.

Finally, DWT is feature extraction technique is based on wavelet analysis. This analysis aims to decompose EEG signals into a certain level and then sub-band energies contained at the last or previous levels to use them as features. DWT uses discrete sampled wavelets and is usually implemented using filters. The signal goes through a high-pass filter and a low-pass filter that are related as quadrature mirror filters. The high-pass filter provides details coefficients and the low-pass filter provides approximation coefficients. After filtering, since half of the frequencies have been removed, a subsampling is applied to reduce the amount of data because only half of the samples are needed to represent the new signal according to Nyquist's sampling theorem [6]. These sets of coefficients represent the signal in different frequency bands. This is a time-frequency domain analysis that is able to provide a representation of power for variable length frequency ranges.

Hardware Platform and Measurement Procedure

The platform in which the selected feature extraction techniques were implemented is a MSP432P401R LaunchPad from Texas Instruments [5]. This development kit incorporates a MSP432P401R microcontroller oriented to develop high performance applications that benefit from low-power operation.

In order to measure execution time, memory usage and power consumption over this platform, a measurement procedure was developed. The measurement of execution time was carried out by using a debugger to get the clock cycles that it took the code to run and then calculating execution time using the operating frequency. For the memory usage, a Memory Allocation tool was used to measure statically allocated memory while dynamic allocated memory usage was calculated by the exploring dynamic memory allocation in the codes. Finally, power consumption was measured using a tool called Energy Trace [4] which is able to provide information about the consumed energy, power, voltage, current and also gives an estimate of the battery life for the current application using a specific type of battery.

Implementation of Feature Extraction Techniques

Each of the feature extraction techniques was implemented, validated and optimized for the microcontroller platform. Some operations necessary for the implementation were achieved by including the CMSIS-DSP Software Library [1] in the design. A real EEG signal was used for the reference simulations and also as an input for the implemented codes. The signal was taken from a dataset created and contributed to PhysioNet [3] by the developers of the BCI2000 [8] [9] instrumentation system that was used to make these recordings. The selected input signal was sampled at 160 Hz, with 512 samples and hence a duration of 3.2 s.

The FIR feature extraction implemented code is able to take an EEG input signal to compute power in any of the frequency bands. The code takes the input signal and performs a FIR filtering for the desired band, then power is computed by taking the square of the signal and finally a moving average filter gets rid of undesired noise. A comparison between the results from the implementation and a reference simulation is provided in figure 2.

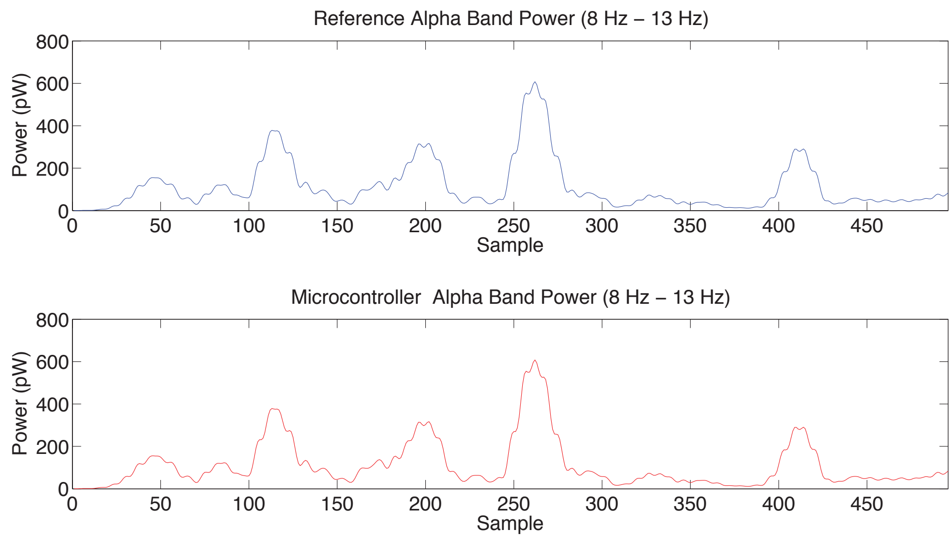

Figure 2. Simulated and microcontroller comparison for FIR

For Welch's method the implemented technique takes the input signal to perform a signal windowing, then a FFT is computed for each of the windows and later a periodogram is calculated for each of the transformed windows, the last step involves an averaging of those periodograms in order to get the final representation of power. The results of Welch's method implementation are depicted in figure 3.

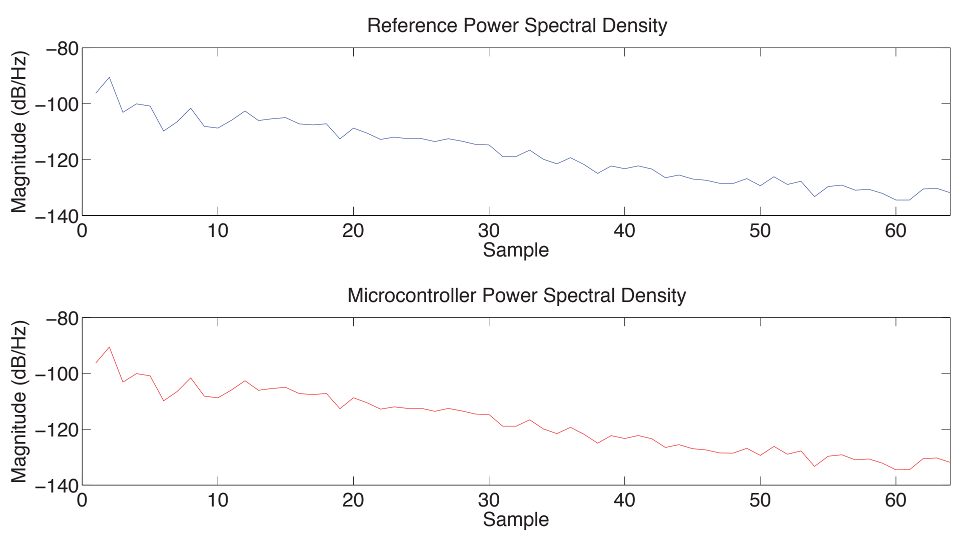

Figure 3. Simulated and microcontroller comparison for Welch's method.

Finally, for DWT the procedure involved the calculation of a bookkeeping vector, then the DWT computation, followed by a rearrangement of coefficients and finally the power computation. The results for DWT are shown in figure 4.

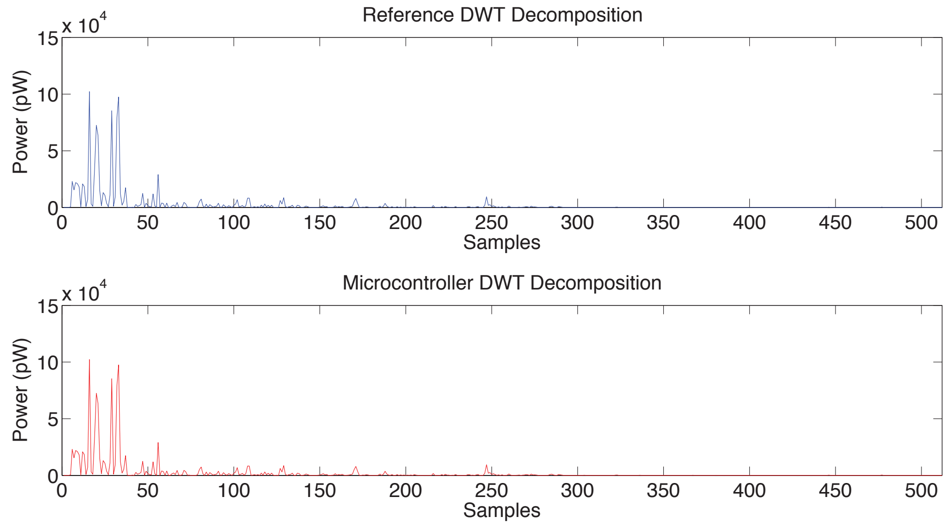

Figure 4. Simulated and microcontroller comparison for DWT.

Every technique was not only implemented but also optimized as much as possible. Execution time and memory usage optimizations were carried out using different tools and settings available for the microcontroller platform while power optimizations were carried out by selecting the best combination of core voltage and operating frequency through a set of measurements.

Evaluation of Feature Extraction Techniques

Execution time, memory usage and power consumption are measured and compared in order to find how the selected techniques perform not only in each specific parameter but also taking them as a whole, keeping in mind that the EEG device should face computation capability and energy capacity in the best way possible.

CPU cycles were measured and time was computed using a known operating frequency. Figure 5 shows the results of the execution time measurements for each algorithm.

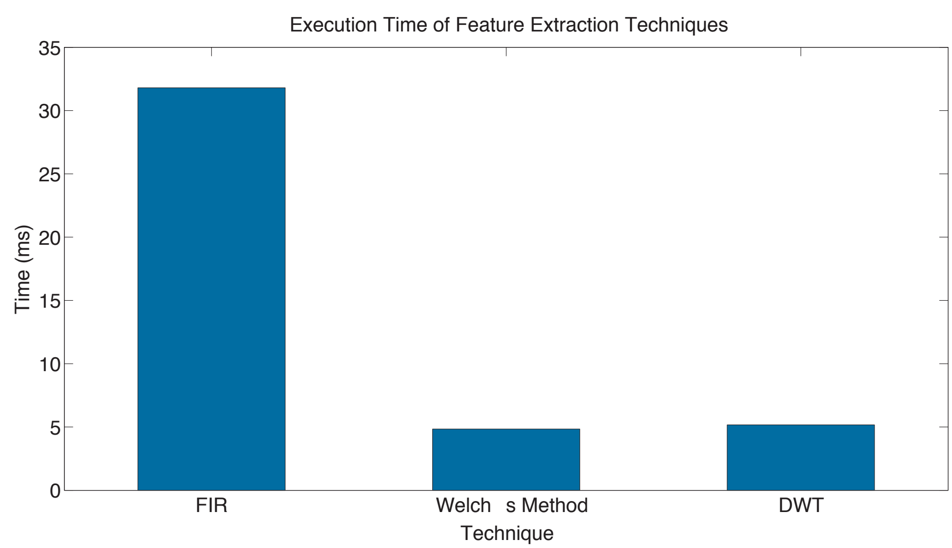

Figure 5. Execution time evaluation.

Flash and SRAM memory usage measurements were performed. Figures 6 and 7 depict the resulting measurements for the Flash and SRAM respectively.

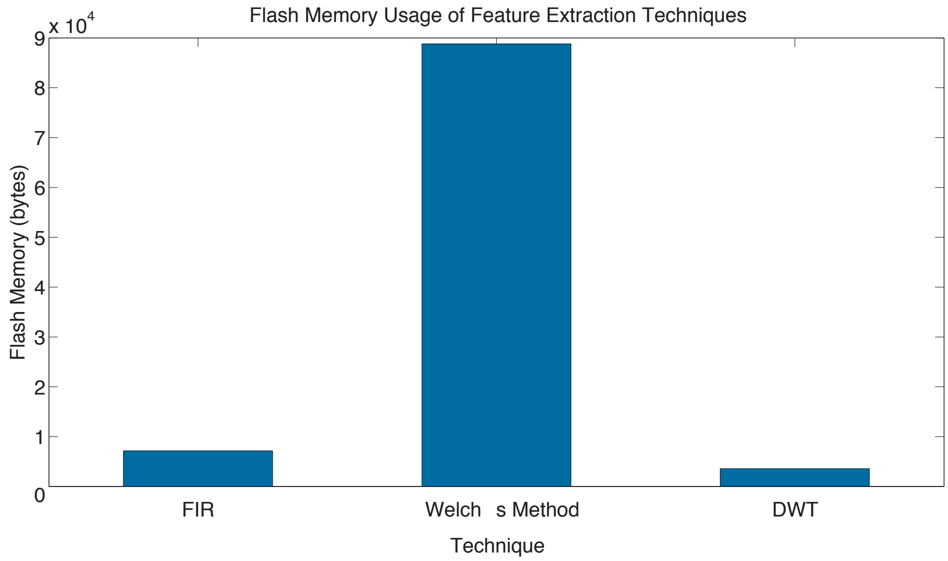

Figure 6. Flash memory usage evaluation.

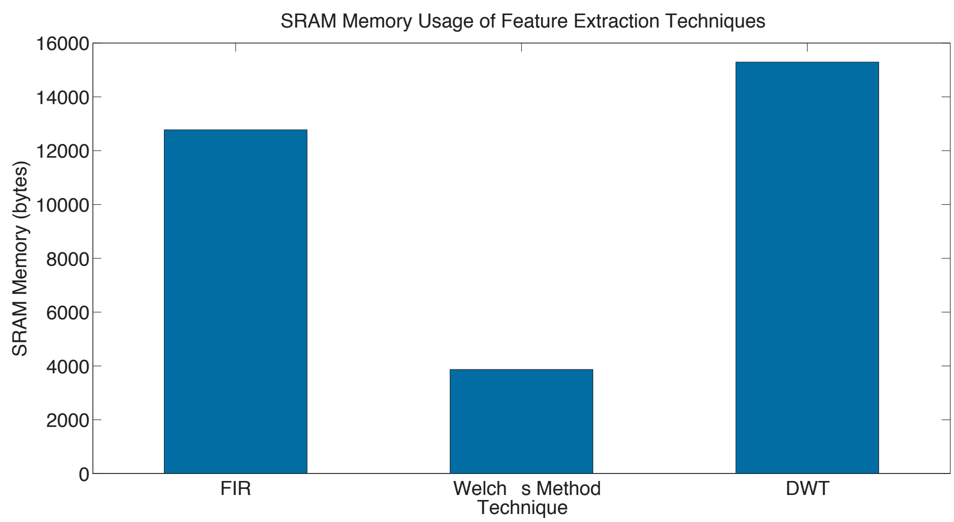

Figure 7. SRAM memory usage evaluation.

To evaluate power consumption both power and energy were measured for each of the techniques. Figures 8 and 9 show a graphical representation of power and energy respectively for each feature extraction technique.

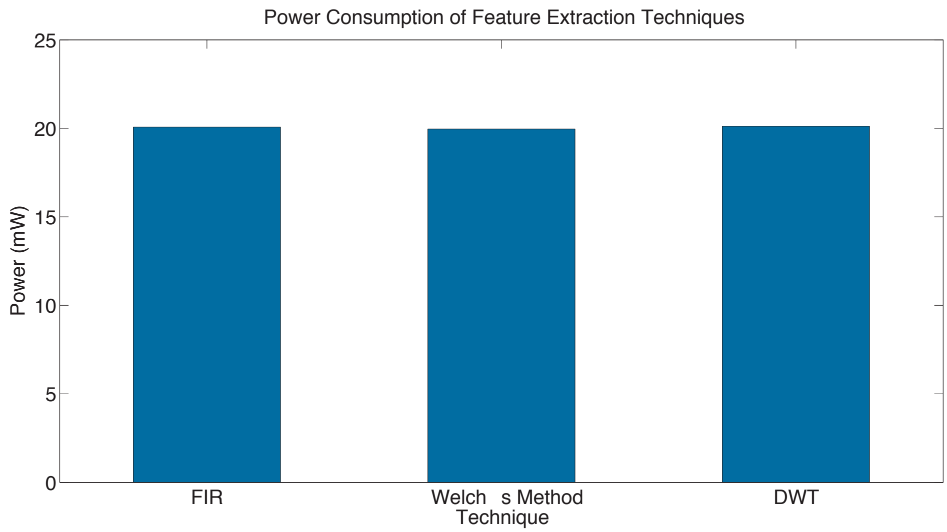

Figure 8. Power consumption evaluation.

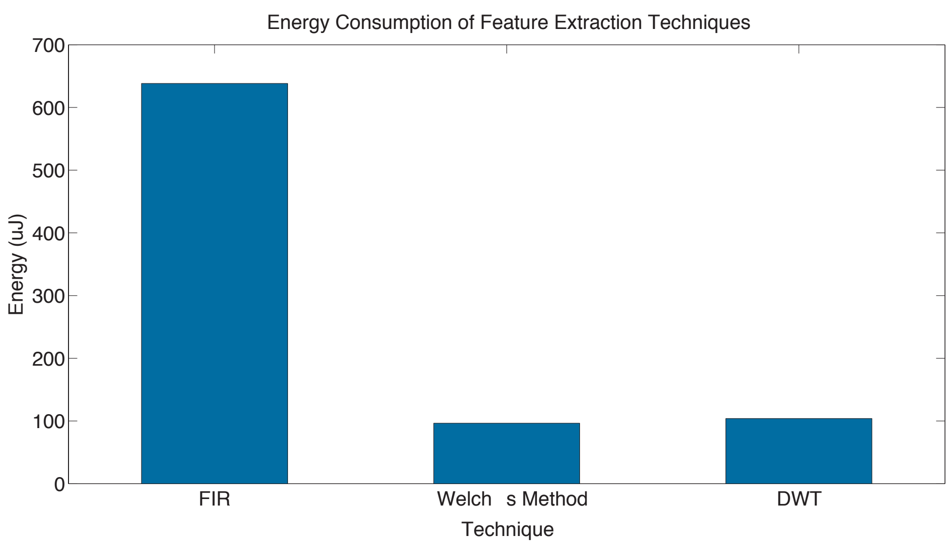

Figure 9. Energy consumption evaluation.

After evaluating each of the metrics in a separate way, it is important then to carry out a general evaluation to put the results together. In terms of execution time, Welch's method and DWT performed similarly between them and considerably better than FIR. For the memory usage, Flash and SRAM were individually analyzed. In terms of Flash memory, DWT and FIR showed good performance while for the SRAM, it was Welch's method which performed better. Power consumption was almost the same for each technique and therefore energy was measured to show similar results to execution time where Welch's method and DWT perform better than FIR.

Conclusions

The evaluation results showed that even though FIR can be used as a feature extraction technique, it may not be the best suited for an IoT implementation due to its poor speed and energy performance. On the other hand, since Welch's method and DWT performed similarly in those fields, the use of one or another will depend on the available resources and implementation. If Flash memory is critical, then DWT is preferred over Welch's method. If SRAM memory usage is critical, Welch's method can suit better the application. Specifically for the IoT EEG, the factor that will determine if Flash or SRAM is critical in the application is the total memory consumption of the rest of the EEG stages.

The importance of this findings rely not only in providing three different implementations of processing cores that are commonly used to extract features from EEG but also in setting a reference of how they behave in different aspects like execution time, memory usage and power consumption. This knowledge is useful in the IoT EEG as well as in any other EEG implementation because any of this cores can be incorporated into the design knowing with certainty their impact in relevant areas. This makes easier the selection of one technique that may fit better in the design based on the final application requirements and available resources.

Future work should incorporate the rest of the EEG stages along with a full application optimization. It would also be interesting to evaluate each technique in terms their actual performance to determine mental states when combined with the other stages in the EEG. In that way, the results of the evaluation presented in this document and a evaluation of performance of the system can lead to a better criteria in order to choose the optimal feature extraction technique for the specific application in which the IoT EEG device will perform. Another suggestion for further work is to explore an alternative hardware implementation (FPGA, ASIC) of the techniques and compare it to the results of the microcontroller implementation presented in this document.

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