Adaptive Sampling for Low-power Wearable and Implantable Devices

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***Abstract*—Wearable and implantable medical devices ranging from wellness monitors to deep brain stimulators are becoming increasingly vital and ubiquitous. Such devices continuously take measurements, which consumes battery. The power consumption is proportional to the amount of information collected and with the frequency of data collection. High power consumption leads to rapid discharging of battery limiting the usage of these devices. These signals are often transmitted wirelessly for analysis, as well as to keep track of the user's record, which also significantly increases power consumption. In this project, we evaluated adaptively modifying the rate of data collection on these devices, in other words, the sampling rate, for electrophysiological monitoring as the relevance of the signal changes in time. We carried out these tests using a proof-of-concept prototype developed for this project. In particular, we reviewed the effects of such adaptive sampling on intracellular potentials, and motor unit action potentials (MUAPs). By doing so, we were able to reduce the amount of data by 48.95% and power by 41.50% for the MUAPs with an 8% sample loss within MUAPs, and by 69.20% and 57.14% for intracellular potentials with a 6.75% sample loss.**

***Index Terms*—Analog-to-digital converters, electrophysiological signal monitoring, wearable devices, implantable devices, low-power.**

I. Introduction

Wearable and implantable medical devices continuously collect electrophysiological data. The extend of their functionality and in the case of many implantable devices — their life span — is dictated by the capacity of their battery. Hence, designing power-efficient components for these devices is at utmost importance for maximizing their functionality and useful life. As these devices become more connected for telemetry, their power consumption becomes even more critical.

The power consumption of typical components of these devices such as signal processing algorithms or transmitters are usually proportional to the size of the input. Once an electrophysiological signal is sensed via a sensor and conditioned with an analog front-end, which typically consists of amplification and filtering circuits, the analog signal is digitized via an Analog-to-Digital Converter (ADC). The ADC ultimately determines the size of the input for the components in the processing chain such as signal processing, machine learning, and transmission via its sampling rate and bit resolution [1].

In most cases, some parts of the electrophysiological signal are more relavant than others. For instance, detecting the shape and timing of action potentials in a Brain-Computer Interface (BCI) is critical. Thus, it is beneficial to BCI applications to acquire the action potentials as accurately as possible, so sampling at the full capabilities of the ADC makes sense.

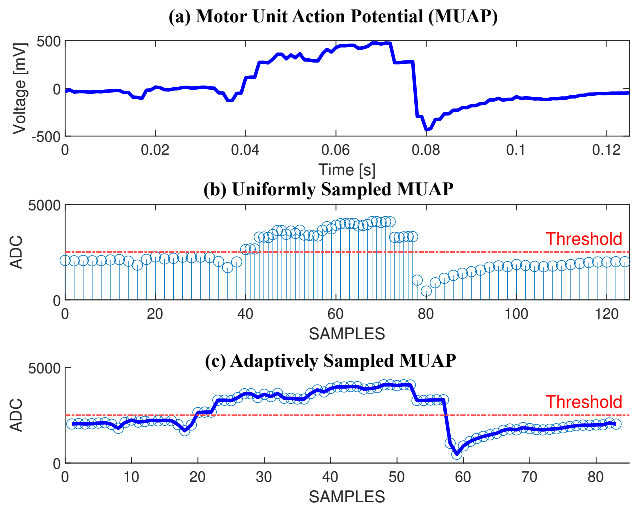

Fig. 1. (a) Amplified Motor Unit Action Potential signal at the input of the ADC. (b) Uniformly sampled ADC. (c) Adaptively sampled MUAP.

Other parts of the signal may not be immediately interesting such as noise. However, these still need to be sampled to determine the noise level, which varies in time. The noise level helps identify which parts of the signal is considered an action potential. In uniform sampling there is no distinction between different parts of the signal, and the entire signal is sampled at the same rate, leading to unnecessary power consumption for sections of the signal that can be read at a lower rate.

Previous work has shown different approaches on how modifications to ADC can reduce power consumption. For instance, Chiang et al. [2] proposed the Tracking Successive Approximation Register (SAR)-ADC in which the unnecessary discharging and charging on the most significant bit (MSb) capacitor are avoided when consecutive samples have the same MSb. As the electrophysiological signals are bandlimited, it is expected that the consecutive samples are close to each other and likely have the same MSb, thus this approach reduces power consumption. Wood et al. [3] proposed predicting ADC, where upcoming sample values are predicted from previous samples using a first order difference equation. As a result, number of comparisons needed to converge to the final sample value is reduced leading to lower power consumption. Chen et al. further improved the prediction methods by self-adjusting the precision of the prediction [4]. Architectures based on level-crossing sampling [5], [6] have successfully been used for biomedical applications [7], where the ADC takes a sample only when one of the predetermined thresholds is crossed. Level-crossing sampling helps reducing the number of samples, thus the total consumption by avoiding sampling if the variation in the signal is low. Compressed sensing is also a very popular general approach to reduce the amount of data [8], however, the asymmetric processing requirement between the transmitter, and receiver affects its complexity [9]. In [10], authors presented simulation results for a signal-adaptive ADC for electrocardiography (ECG). Their approach does not consider the noise level, thus susceptible to variations in noise. Chen et al. proposed a design that defines a range of sampling frequencies of the ADC according to the change in amplitude of the signal. In order to achieve a further decrease of transmission power consumption, the sampled data is then compressed using a lossless data compression technique. However, this technique lacks the telemetry approach proposed on this paper, which allows real-time data monitoring [11].

In this paper, we present a proof-of-concept discrete prototype (Fig. 2) for adaptive sampling of electrophysiological signals. We evaluated the reductions in power consumption for action potentials taken from hippocampus neurons [12], [13], and motor units[14]. The adaptive sampling approach evaluated in this paper is based on [15] and illustrated with an example in Fig. 1 using motor unit action potential (MUAP). MUAPs are electrical potentials in muscles during their contraction, representing muscular activities [16]. Fig. 1(a) shows the original MUAP as a continuous signal, where the MUAP appears between time 40 and 80 milliseconds. In this example, the MUAP is identified as the portions of the signal above a predetermined voltage threshold (dotted horizontal line). Fig. 1(b) shows the same signal digitized after a conventional analog-to-digital conversion with uniform sampling, where the samples are taken periodically at fixed time intervals. In the digitized signal the MUAP appears approximately between sample 40 and 78, spanning 39 samples. The regions around the MUAP only consists of noise and useful for determining the threshold value as the threshold value varies in time and is typically taken as the function of the variance of noise for a given time period [17]. However, sampling the noise at the same rate as the MUAPs is unnecessary. Yet, uniform sampling makes no distinction between the noise and MUAPs, causing noise to be sampled at a high rate. This results in higher number of samples and increases the power consumption of ADC, signal processing, and transmission. Fig 1(c) illustrates the proposed approach, where the signal is sampled at a reduced rate when there is no MUAP, and only sampled at full rate when there is an MUAP (between samples 19 and 58). In the example the total number of samples is reduced from 122 to 83, saving a third of the samples while digitizing the MUAP with the exact number of samples as the uniform sampling. The selection of when to use the full rate or the reduced rate depends on the application. We provide a proof-of-concept method for this selection in Section II. In Section III, the performance of our prototype is summarized. Section IV concludes the paper.

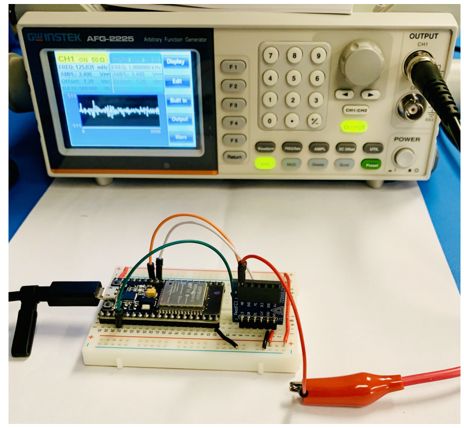

Fig. 2. Experimental Setup.

II. Adaptive Sampling for Action Potentials

A. Adaptive ADC

To reduce unnecessary sampling, we first need to determine if a sample belongs to a relevant part of the signal. On a well-designed acquisition system action potentials have peak amplitudes above the noise level. Thus, a thresholding mechanism can be sufficient to distinguish the action potential (relevant signal) from the background noise (less relevant signal).

In our previous work [17], we developed a custom action potential (i.e., spike) detector circuit which can distinguish the spikes from the noise by means of a spike detection threshold. In the current work, we propose and implemented a similar detector in embedded software, by defining a threshold in the microcontroller of our data acquisition system, and reducing the sampling rate of the ADC when the signal is below the threshold. We use a spike detection threshold typically two standard deviations above the noise level. However, as the noise level changes, the threshold calculations should be repeated to avoid missing spikes. This dynamic threshold calculation is left as future work. When the instantaneous value of the incoming signal is above a threshold, it will indicate that there is an Action Potential (relevant signal), thus it will adapt the Analog-To-Digital converter to operate at its full sampling speed. This means the ADC will take a sample next at the time as if it is a uniform ADC. However, if the current sample is below the threshold (less relevant), the sampling rate is reduced by the proposed system. This effectively is similar to skipping one or more samples following the current sample, if a uniform sampling ADC was used. This reduced sampling rate is still useful to determine the variations in noise level. Fig. 3 shows a flowchart of this sample rate adaptation process.

B. Hardware Implementation

We implemented the proposed adaptive data acquisition system using an ESP32-WROOM-32D microcontroller with integrated WiFi and dual-mode Bluetooth [18] and a 12-bit external ADC (Analog Devices AD74746A on a Digilent Pmod AD1) [19]. The microcontroller is configured to run at a clock rate of 240 MHz, with a 4 MB Flash memory

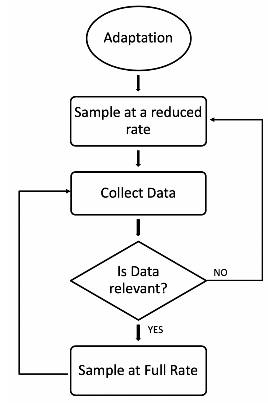

Fig. 3. Adaptation Block.

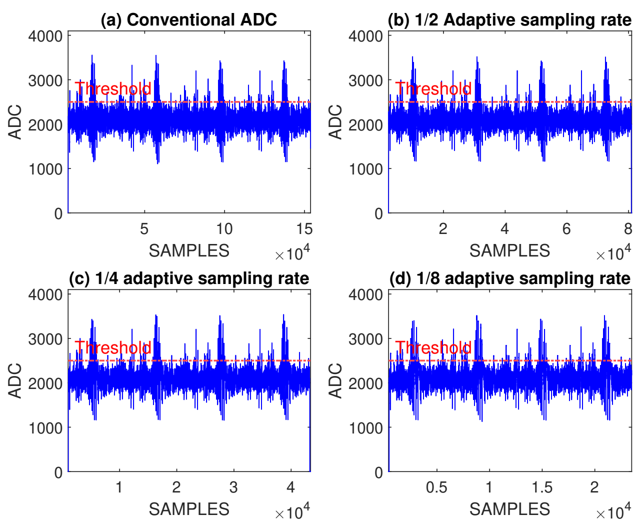

Fig. 4. A signal sampled with and without adaptive ADC. (a) MUAP signal sampled with a conventional ADC at full rate. (b) Same signal sampled with adaptive ADC at half rate when signal is below threshold. (c) The signal with adaptive ADC at 1/4 rate. (d) Same signal with adaptive ADC at 1/8 rate.

running at 80 MHz, and a 520 KB SRAM. The microcontroller communicates with the ADC via a Serial Peripheral Interface (SPI). The external ADC is clocked with a 20 MHz SPI clock and has a reference voltage of 5V.

The firmware for the microcontroller is developed using the Arduino IDE, and it consists of three main components: (1) Data acquisition, (2) adaptation block and, (3) transmission. The data acquisition component consists of ADC configuration function, and interrupt routines for sampling the data. For the purpose of the current work, as a proof-of-concept, the adaptation block simply compares the current sample with a threshold and determines how long to wait before the next sample. The acquired data is transmitted through Wi-Fi using User Datagram Protocol (UDP) packets to a server for further analysis. Multiple samples are transmitted within each packet, specifically, 32 samples per UDP packet.

III. Performance

Here, we present the results from our proof-of-concept prototype. We evaluated data and power savings, and signal quality for representative MUAP and intracellular signals.

A. Reduction in Number of Sampling Process

1) MUAP: We have compared our proposed adaptive ADC with a conventional ADC, as shown in Fig. 4. For both ADCs, the same input signal is applied by replaying the MUAP signals [14] with an arbitrary waveform generator. The original input signal consists of 4096 samples sampled at 500 Hz corresponding to a 30 seconds of recording. The input signal is already amplified. With the conventional ADC running at 5kS/s, the input is sampled using a total of 153,000 samples. Our proposed ADC, with sampling rate of 5kS/s, which drops to 2.5kS/s (i.e., half rate as the adaptive sampling rate) for epochs deemed less important (e.g., noise) reduced the total number of samples to 78,100. Further reduction in the adaptive sampling rate to 1/4 and 1/8, decreased the total number of samples to 42,200 and 23,000, respectively. Thus, for adaptive sampling rate at 1/2, 1/4, and 1/8 of the original sampling rate, there is a reduction by 48.95%, 72.42%, and 84.97% in number of samples, respectively. The overall savings will be a function of the density of action potentials in the signal. However, this example is representative of the general case.

2) Intracellular Potentials: Similarly, we have compared our proposed adaptive ADC with a conventional ADC when sampling intracellular potentials [12], [13]. The input signal is applied same as before, by replaying the intracellular potentials with an arbitrary waveform generator, consisting of 4096 samples sampled at 500 Hz corresponding to a 30 seconds of recording. Note that due to the limitations of our signal generator, we reduce the speed of the signal. The same conventional ADC (5 kS/s) sampled the input signal using a total of 150,000 samples. Our proposed ADC, with adaptive sampling rate of 1/2, 1/4, and 1/8 reduced the total number of samples to 81,500 (reduction of 45.67%), 46,200 (reduction of 69.20%) and 26,100 (reduction of 82.6%), respectively.

3) Signal Quality: We evaluated our proposed approach for signal quality loss, where we define this loss as percentage of samples that belong to a relevant part of the signal (e.g., part of a spike), which are missed due to adaptation. Our proposed ADC when sampling MUAP signals, with adaptive sampling rate of 1/2, gives us a signal quality loss of 8%. Further reduction in the adaptive sampling to 1/4 and 1/8, increases this loss to 11.7% and 23.5%, respectively. When sampling intracellular potentials, the signal quality loss is 0.84% at 1/2 rate, 6.75% at 1/4 rate and 27% at 1/8 adaptive rate. This shows that especially at higher adaptive rates (e.g. 1/2 for both or 1/4 for intracellular potentials) the loss is acceptable and can be traded off for power reduction.

B. Power Consumption

1) MUAP: The power consumption of the ADC when sampling MUAP signals is shown in Table I. The baseline power consumption for the microcontroller without the ADC

TABLE I
POWER CONSUMPTION OF THE ADC AND WIFI FROM A 5V POWER SUPPLY WHEN SAMPLING MUAP SIGNAL

	Normal ADC	1/2 Rate	1/4 Rate	1/8 Rate
No Wi-Fi	10.6 mA	6.2 mA	5.2 mA	4 mA
ADC-only power reduction (%)		**41.50%**	**50.94%**	**62.26%**
Wi-Fi	280 mA	242 mA	190 mA	153 mA
Wi-Fi power reduction (%)		**19%**	**45%**	**63.5%**

TABLE II
POWER CONSUMPTION OF THE ADC AND WI-FI FROM A 5V POWER SUPPLY WHEN SAMPLING INTRACELLULAR POTENTIALS.

	Normal ADC	1/2 Rate	1/4 Rate	1/8 Rate
No Wi-Fi	10.5 mA	5.6 mA	4.5 mA	3.7 mA
ADC-only power reduction (%)		**46.67%**	**57.14%**	**64.76%**
Wi-Fi	278 mA	233 mA	177 mA	147 mA
Wi-Fi power reduction (%)		**16.19%**	**36.33%**	**47.12%**

and no Wi-Fi transmission is 80 mA@5V (400 mW). With the conventional ADC without data transmission the power consumption is 90.6 mA@5V (the conventional ADC consumes 10.6 mA@5V in addition to the 80 mA@5V baseline). When the adaptive rate is used, the ADC power consumption is reduced to as low as 4 mA@5V, when the adaptive sampling rate is at 1/8, which is an ADC power reduction of 62.26%. When, the Wi-Fi transmission of the data is also considered, the reduction in power consumption by using the adaptive rate is as high as %63.50 compared to a traditional ADC.

2) Intracellular Potentials: When sampling intracellular potentials, the ADC power is reduced to as low as 3.7 mA, when the adaptive sampling rate is at 1/8, which is an ADC power reduction of 64.76%. When transmitting the data over Wi-Fi the reduction in power consumption by using the adaptive rate is up to 47.12% compared to a traditional ADC.

IV. CONCLUSION

In this work, we have implemented an adaptive Analog-to-Digital Converter that reduces the sampling rate when it detects that the input signal is not of relevance according to its application. With this approach, we were able to reduce the amount of data collected and transmitted as well as power consumption while keeping the signal quality similar to the uniform sampling. For our future work, we will develop our adaptation approach further to improve the trade-off between the power and data savings and signal quality.

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