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An Accuracy Aware Low Power Wireless EEG Unit with Information Content based Adaptive Data Compression

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Abstract— **We present a digital system for adaptive data compression for low power wireless transmission of Electroencephalography (EEG) data. The proposed system acts as a base-band processor between the EEG analog-to-digital front-end and RF transceiver. It performs a real-time accuracy energy trade-off for multi-channel EEG signal transmission by controlling the volume of transmitted data. We propose a multi-core digital signal processor for on-chip processing of EEG signals, to detect signal information of each channel and perform real-time adaptive compression. Our analysis shows that the proposed approach can provide significant savings in transmitter power with minimal impact on the overall signal accuracy.**

I. Introduction

Wireless Electroencephalography (EEG) systems are emerging as an efficient medical tool for long-term prolonged monitoring of EEG signals and are used to diagnose epilepsy, sleep related disorders etc. In these systems, an EEG acquisition unit (often a headset) continuously acquires the EEG signals and transmits the data wirelessly to a remote host. The wireless system provides the comfort of no wired connections, allowing the patients to return to their natural environment (where seizures originally occur). The storage space for data is virtually unlimited, as results are directly transmitted to a local host computer or device. However, a primary concern for deploying wireless EEG systems is in the power dissipation and the battery life-time. Yates et. al. has shown that Radio Frequency (RF) transmission of data dominates the total power of wireless EEG units even for short-range (Bluetooth) transmission. Methods have been proposed to reduce the volume of the transmitted data, because it can translate into a significant reduction in energy consumption [1]. By reducing the volume, we effectively reduce the time that the transceiver operates and hence, saves power.

In this paper, we propose a multi-core digital system to adaptively compress multi-channel EEG signals, by determining the compression rate based on the information content. The digital system detects the information content of EEG signals of each channel independently and performs adaptive compression. The proposed system aims to preserve the generic behavior of the signal by transmitting compressed data for background EEG and uncompressed data during regions of interesting (epileptic or spike related) activity. The continuously transmitted EEG signal is available for EEG interpretation which provides the EEG interpreter a better opportunity for correct diagnosis. By transmitting low-power, low-quality data during background EEGs, and high-power, high quality data during 'important' regions, the method of 'adaptive compression' will provide a dynamic energy-accuracy tradeoff.

II. Background

The primary challenge in the data compression for EEG transmission is the conflicting energy and accuracy requirements. Schemes for fixed compression of EEG data transmission have been proposed, but there are limitations. For fixed (or full) compression of data, increasing the compression ratio reduces the accuracy of the represented signal. A higher compression also reduces the data volume and energy as well. For EEG systems, the epileptic activity, that is signals exhibiting behavior in the form of 'spikes' and sharp waves, needs to be accurately transmitted. Hence, the compression ratio needs to be chosen to reduce the errors for spike related regions. Unfortunately, as the occurrence probabilities for spike events are rare for long-term monitoring, significant energy is lost by transmitting background EEG signal with more-than-necessary accuracy. On the other hand, if a higher compression ratio is chosen to reduce energy during background transmission, the spike related activity will be transmitted with less-than-required quality making it more difficult for an EEG interpretation. Therefore, a run-time dynamic trade-off of energy and accuracy is not possible in a "Full Compression" system.

To eliminate this challenge, 'Discontinuous' transmission was proposed as an event related solution, to present the neurologists with only events that include epileptic and spike related activity [1]. During this time, the acquired signal is directly transmitted as high quality data via the transceiver. When these periods do not exist, the channel is cut off, and no data is transmitted. This method provides very low energy but does not consider the accuracy in all regions. It has been noted that the analysis of EEG records are subjective, often requires background information as well, and most neurologist disagree about what is considered epileptic activity [5]. Moreover, algorithms to select 'relevant' activity are imperfect, and as a result false-positives and false-negative spike detections exist. By removing data points for analysis, this will further increase the difficulty to characterize EEG signals and spike related events. Thus, in the presence of false-negative detection, the

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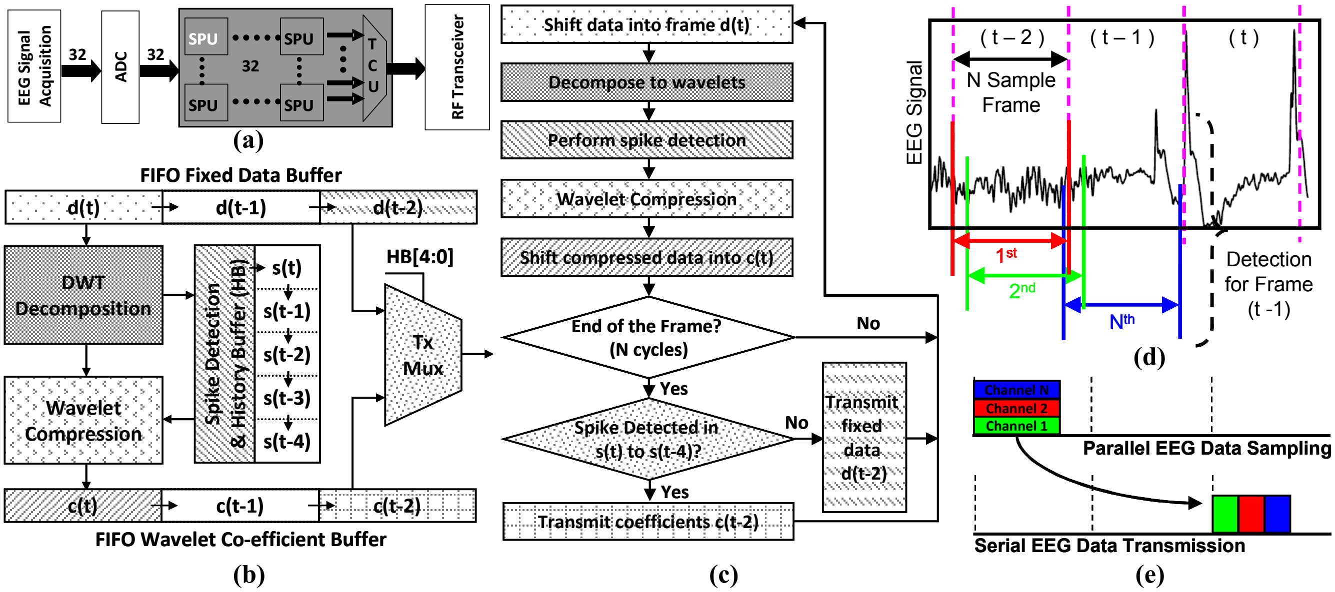


Fig. 1: (a) The proposed digital implementation of a wireless 32-channel EEG system. A multi-core system was chosen for the potential to exploit parallelism in multi-channel detection and analysis. (b) Signal Processing Unit (SPU) unit to detect and compress data so that is can be sent to the TCU for time division multiplexing. (c) Algorithm of the SPU (fig b) used to process EEG signal for one channel. Shaded boxes are used to denote complementary steps/blocks. (d) Shift and detect scheme for high resolution spike detection. The sliding window will make N detections on a frame of N samples. (e) The 32-channel EEG signals will be sampled in parallel and after processing time multiplexed before transmission.

error can be catastrophic as no information will be presented to the EEG interpreter.

III. System Design And Methodology

To overcome challenges related to the two proposed methods above, we are proposing to transmit with the best accuracy-energy tradeoff. During spike related events, it is necessary to transmit EEG signals with the highest quality to preserve accuracy. At other times, the accuracy is not as important, so we will transmit compressed versions of the data that provide a low power transmission scheme and still allow the signal behavior to be recognized. This section introduces our proposed architecture for adaptive compression, and it is applicable to other scenarios besides EEG transmission. The system acts as a digital base-band between the EEG front-end acquisition and RF transceiver.

A. Overall System Objective

Single channel EEG implementations exist, but for a thorough system that is applicable in Epilepsy outpatient procedures, 16 to 32 channels are necessary. For this reason, we have focused on multi-channel EEG transmission. Figure 1(a) depicts the overall goal of the proposed system. Thirty-two acquisition units are used to obtain data at different locations, and they are then converted to digital signals with the Analog-to-Digital Converter (ADC). The gray block is emphasized to denote the design focus of this work. In order to detect epileptic or 'interesting' activity, an on-chip implementation of a complex algorithm is required. To improve the detection methods, multi-channel analysis, where each node is dependent, can be performed. In response to the demand for complex and parallel algorithms, it is possible to use a digital system that exploits multi-core processing to complete this task. Previous works have attempted analog implementations of wireless EEG systems, but a thoroughly investigated, custom digital system has the potential provide performance and power benefits [6-9]. Additionally, only generic studies of digital implementations have been done, showing skewed results that support analog over digital systems [7]. The network of these digital cores or Signal Processing Units (SPUs) receives its input from the ADC. Once the processing is complete, data is time-multiplexed and transmitted to a receiver station via the Transmission Control Units (TCU) and RF Transceiver.

B. Signal Processing Units

The micro-architecture of the SPU for a single channel is depicted in Figure 1(b). Each SPU processes data on a frame-by-frame basis, where a frame is a collection of N samples. If a spike is not detected within the frame or neighboring frames, the data is compressed and eventually transmitted. When a spike is detected in the frame (or neighboring frames) the data is directly transmitted, producing a high quality result. Neighboring frames are relevant for epileptic activity, because they can provide the EEG interpreter insight into behavior before and after spikes occur. In each cycle data is shifted into the FIFO fixed data buffer via d(t). The FIFO d(t) holds the last frame (or N samples) of data, and every cycle spike detection and data compression is performed using wavelets. Note that we perform EEG detection every cycle (N detections for a frame size of N samples). If a spike is detected at least once, the entire frame is classified as epileptic activity. Figure 1(d) summarizes this shift and detect scheme. This scheme results in an inherent redundancy in detection and reduces the number of false negative detections. A false negative is an incorrect classification of a feature as a non-feature, in our case epileptic spikes. Although the shift and detect scheme

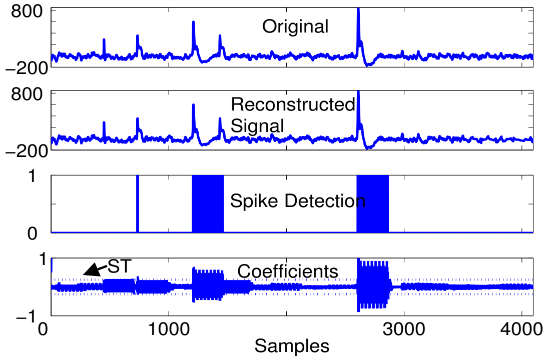


Fig. 2: Digital Adaptive Compression System functionality with simple spike detection. Spikes are detected when the wavelet coefficients surpass the Spike Threshold (ST).

increases the energy required for computation, it improves the overall system accuracy.

After detection, compression is performed on the incoming EEG signal on frame-by-frame basis (i.e. compression is performed on consecutive non-overlapping frames.) The compressed data will be represented in the wavelet domain, and these co-efficients are then stored in another FIFO buffer, c(t). At the end of the frame, the spike detection result for the entire EEG frame is stored in the History Buffer, HB. When the frame at time (t) has completed, the frame in (t-2) is ready for transmission. This delay will allow for optimal transmission, by considering the epileptic activity in neighboring frames: (t), (t-1), (t-3), and (t-4). Based on the result of the detection, the high quality frame, d(t-2), or the compressed frame, c(t-2) will be sent to the TCU for transmission.

C. Spike Detection and Compression with Wavelets

The method of spike detection and data compression were performed in wavelet domain to isolate the frequency bands associated with multi-level resolution [10]. Both the method of compression and detection were based on a simple thresholding technique. For spike detection, if the magnitude of the wavelets in a frequency band surpassed the spike threshold (ST), epileptic activity was detected. For data compression, all the wavelets that are below the compression threshold (CT) were removed. The resulting method of compression is data dependent, and indeed the system results will be based on the selection of the ST and CT. In this paper, to show the feasibility and advantage of 'adaptive compression', we have considered simple techniques for detection and compression. The results encourage a more thorough investigation of complex detection and compression algorithms [4][11-12] to be performed in future work. Figure 2 shows how spike detection is performed, comparing the original and reconstructed signals. The pre-recorded EEG data available in [13] was used in the analysis.

D. Synchronization of Acquisition and Transmission

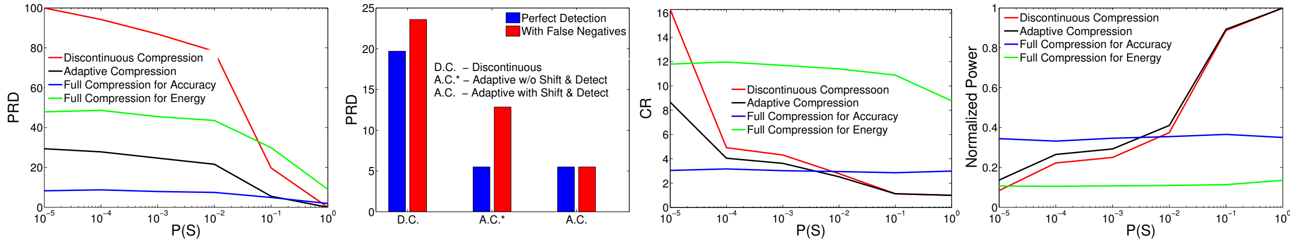
The data from an EEG sensor will enter the proposed system through the ADC, and processing will be performed on a frame by frame basis (Recall an 'EEG frame' is N samples long.) For 32 channel operation, we consider input frames are received and processed by their corresponding SPU in parallel. After processing, each SPU will generate the transmission frame corresponding to its channel. Depending on the spike activity, these frames can be compressed of decompressed versions of data. A transmission control unit (TCU) sequentially collects the transmission frames of each channel and creates a bit-serial data-payload for the RF transceiver. See Figure 1(e) for details. It should be noted that a data payload for the RF transmission is collection of 32 transmission frames. The transmission of each data payload is synchronized with each new EEG frame acquisition. This is possible considering the low sampling rate of EEG signals (150-250Hz) and high data rate of transceivers (~1Mbps). For example, considering a frame size of N=1024, 32 EEG channels, 16bit data, and sampling frequency of 250Hz, results in acquisition time of 4.096 seconds and 0.5Mbit of data. For a RF transceiver with 1Mbps data rate, the transmission of the data pay-load will require ~0.5seconds. Hence, parallel EEG acquisition with serial data transmission is a completely viable approach.

IV. RESULTS

In this section we compare the accuracy and energy considerations of our 'adaptive compression' method versus previous data reduction methods described in the background section: 1) Discontinuous, 2) Full Compression optimized for energy and 3) accuracy. Since the above metrics will vary based on the data presented, we have taken actual EEG data from [13], and used it to generate our own signals based on the Probability of Spike occurring within a frame, P(S). Background EEG patterns were selected based on a normal random distribution, and epileptic signatures were inserted in time. The analysis of the compression methods over the wide range of P(S) will show the expected behavior in all scenarios.

A. Accuracy Considerations

Figure 3(a) shows the Percent Root Mean-Square Difference (PRD) for the reconstructed signal and original signals for the four compression methods. A perfectly reconstructed signal occurs when the PRD is zero. The first thing to note is that the full compression methods (blue and green), have a limited dynamic range of accuracy once the system is designed. On the contrary, the discontinuous and 'adaptive' methods, can alter there accuracy over a wide range to achieve ideal reconstruction the presence of spike activity. The advantage of the 'adaptive' method is that even when the spike activity is not detected, the general signal behavior is still transmitted. This is particularly important when the discontinuous method detects a false negative (FN). Once this information is cutoff from transmission, it is lost, providing less useful data for the EEG interpreter. Figure 3(b) shows how the accuracy of the discontinuous and adaptive methods behaves in response to false negatives. As it is expected, in the presence of FNs, the discontinuous method has worse accuracy, (larger PRD). On the other hand, with the shift and detect scheme, the accuracy is virtually unaffected by of false negatives.



(a) **(b)** **(c)** **(d)**

Fig. 3: (a) Accuracy comparisons show that discontinuous does not provide great accuracy in all regions. The adaptive method is advantageous for its wide range of accuracies. (b) False Negative scenarios show that the discontinuous method can reduce accuracy, while the shift and detect scheme with adaptive compression virtually eliminates the effect. (c) Compression ratios for the four compression schemes. (d) System Power measurements for the four schemes show that if we expect random instances of epileptic activity, the adaptive method will stay in the low power mode more often than not.

B. *Energy Considerations*

Figure 3(c) shows the how the Compression Ratio (CR) of the methods are altered depending on the P(S). Once again full compression (blue/green) methods have limited dynamic range, but this time being compression ratios. This means that care must be taken when designing the system with full compression methods. If the definition of spike or its occurrence probability changes dynamically, the original design choice restricts the energy-accuracy trade-off. The proposed adaptive compression system has the potential to provide high compression during background EEGs, and high accuracy during epileptic activity.

For moderate data rates (~1Mbps) the transmission power is determined by the transceiver electronics [3]. Better energy-efficiency is achieved by transmitting data at the highest possible data rate and putting the system into idle (sleep) mode for longer duration (duty cycle control) [3]. The average power considering data compression ratio can be defined as the contributions of idle, switching and transmission power:

$$P_{avg} = \frac{P_{idle}t_{idle} + P_{tx}t_{tx} + P_{switch}t_{switch}}{t_{idle} + t_{tx} + t_{switch}} \quad (1)$$

$$t_{tx} = \frac{L_{pkt}}{r \cdot CR} \quad (2)$$

where r is the data rate, and L is the length of the input packet. A higher CR reduces the transmission time and allows the system to be in idle mode for longer time thereby reducing the average transmission power. Figure 3(d) shows the normalized average power for the four compression methods, using the power and time measurements of a low power NRF2401 Nordic transceiver [14]. These results show the inverse trend of CR. The main point here is that when there is no epileptic activity (P(S) is low), the adaptive compression method dissipates less power. Upon detecting activity, the power is increased nearly 4X to transmit high quality data. In general, if we expect random instances of epileptic activity, the adaptive method will stay in the low power mode more often than not. Note that the sensor, ADC, and the proposed signal processing unit will consume less than 1mW of power. This is more than 10X lower than the power consumption of the transceiver for medium range communications (> 10 meters) [3].

V. Conclusion

In conclusion we have presented an alternative approach to data reduction for use in a wireless EEG system. Compared to previous compression methods, adaptive compression provides high power, very accurate data transmission during epileptic activity and low power, less accurate transmission during background EEGs. We have also introduced a new shift and detect scheme for spike detection that is unique to digital systems and increases detection accuracy, by eliminating false negatives. By presenting a custom digital system approach to EEG processing, we can take advantage of parallelism and high throughput when complex algorithms are implemented. The preceding analysis gives and encouraging results into digital EEG systems and the use of adaptive compression as well.

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