Energy Efficient Acquisition and Reconstruction of EEG Signals

W. Singh, A. Shukla, S. Deb and A. Majumdar

Abstract- **In Wireless Body Area Networks (WBAN) the energy consumption is dominated by sensing and communication. Previous Compressed Sensing (CS) based solutions to EEG tele-monitoring over WBAN's could only reduce the communication cost. In this work, we propose a matrix completion based formulation that can also reduce the energy consumption for sensing. We test our method with state-of-the-art CS based techniques and find that the reconstruction accuracy from our method is significantly better and that too at considerably less energy consumption. Our method is also tested for post-reconstruction signal classification where it outperforms previous CS based techniques. At the heart of the system is an Analog to Information Converter (AIC) implemented in 65nm CMOS technology. The pseudorandom clock generator enables random under-sampling and subsequent conversion by the 12-bit Successive Approximation Register Analog to Digital Converter (SAR ADC). AIC achieves a sample rate of 0.5 KS/s, an ENOB 9.54 bits, and consumes 108 nW from 1 V power supply.**

Index Terms— EEG, WBAN, Compressed Sensing, Analog-to-Information Converter, SAR ADC

I. Introduction

EEG signals are useful for monitoring brain activities for medical (seizure detection) and cognitive tasks (emotion recognition, Brain Computer Interface). In recent times there is a growing interest in tele-monitoring of EEG signals using Wireless Body Area Network (WBAN). The main challenge in a WBAN is to conserve energy; energy is consumed by three tasks - sensing, processing and communication. The communication cost is the highest; the sensing cost is also significant for our problem; the processing cost is negligible compared to the other two tasks.

As communication is the most power hungry operation, the primary target till now has been to reduce it by some form of signal compression. However, traditional transform coding techniques are too computing intensive for a simple sensor node and have been precluded at the onset. One easy way to compress the signal is to project it to a lower dimensional matrix by using a random matrix. It has been shown in recent studies [1, 2] that a binary random ensemble (of 1's and 0's) is effective for this task, since storing and operating on such a sparse matrix is efficient.

Recovering the EEG signal from its lower-dimensional projection is a challenge. Non-linear recovery algorithms based on Compressed Sensing (CS) need to be employed. Since, the signal recovery takes place at the base station, this is not a challenge as computing power (at the base) is not at a premium.

Previous works could reduce the communication energy in a computationally efficient manner, but could not reduce the sensing energy. The only way to reduce sensing energy is by under-sampling the EEG signal. Periodic under-sampling is not an option for obvious reasons. Even with random under-sampling, CS based techniques are unable to recover the signal. CS requires the sampling operator (in this case the Dirac basis) to be maximally incoherent with the sparsifying basis (Wavelet or Gabor for EEG). Unfortunately this condition is not satisfied, i.e. wavelet and Gabor basis is not very incoherent from the Dirac sampling basis. Thus CS based techniques fail. This is the main reason, why past researchers were unable to reduce the sensing energy.

For the first time in this work, we propose a technique for reducing the sensing cost in EEG signal acquisition. There are two associated problems:

1. What should be the signal reconstruction algorithm?
2. How to design an efficient Analog-to-Information Converter (AIC) for the said scenario?

The detailed answer to both these problems are discussed later, but here is the brief answer to the first problem. EEG signals are always acquired via multiple channels. The signals from all the channels are correlated. These correlated signals can be stacked as columns of a matrix; the thus formed matrix is low-rank since the columns are not independent. Since each of the signals are randomly under-sampled, the full matrix is not available - therefore the problem is to recover this low-rank matrix from its under-sampled entries. This is a classical low-rank matrix completion problem [3].

An elaborate discussion on our proposed signal reconstruction is given in the following section. Owing to limitations of space we are unable to discuss prior studies in CS based EEG signal reconstruction in section II. The design of the data acquisition hardware is described in section III. We discuss the experimental results in section IV. Finally the conclusions of this work are discussed in section V.

II. EEG Signal Reconstruction

As we mentioned before, the only way to reduce acquisition energy is by under-sampling the EEG signals. This operation can be expressed as:

$$y_i = R_i o x_i + \eta, \ \forall i \tag{1}$$

where i, denotes the i^{th} channel, x_i is the EEG signal (to be reconstructed), y_i is the under-sampled measurement, R_i is the binary sampling mask (o denotes bit-wise multiplication) and η is the noise assumed to be Normally distributed.

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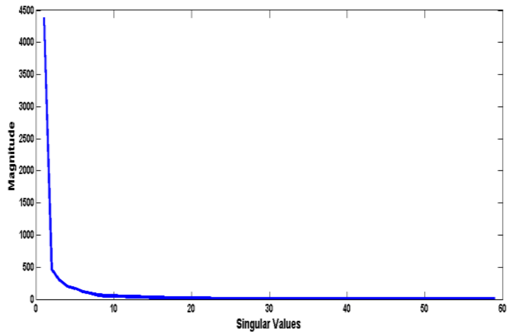

Fig. 1 Decay of singular values for multi-channel signal ensemble.

The EEG signal ensemble from all the channels can be arranged in the following form:

$$Y = R \, o \, X + \eta \quad (2)$$

where Y, X and R are the Casorati matrices formed by stacking the y_i's, x_i's and R_i's as columns.

The problem is to recover X from the acquired Y and knowledge of R. This is an under-determined inverse problem with infinitely many solutions. To find a reasonable solution, we need to have prior knowledge regarding X. In this case, we model X to be a low-rank matrix. This is true, since the EEG signals from different channels are correlated with each other; therefore the columns of X are not linearly independent. In order to corroborate our claim, we show the decay of singular values of a multi-channel EEG ensemble in Fig. 1. The singular values decay fast, implying that the signal ensemble is approximately low-rank.

In low-rank matrix completion [3], one ideally needs to minimize the rank of the matrix. However, rank minimization is an NP hard problem. Theoretical studies [3, 4] have shown that, relaxing the NP hard rank minimization problem to its closest convex surrogate - Nuclear Norm, still guarantees a low-rank solution. Following these studies, we propose to recover X via:

$$\min_{X} \left\| Y - R \, o \, X \right\|_F^2 + \lambda \left\| X \right\|_* \quad (3)$$

Here 'F' denotes the Frobenius' norm and '*' denotes the Nuclear Norm which is defined as the sum of singular values.

There are several algorithms to solve the low-rank matrix recovery problem, e.g. Singular Value Thresholding (SVT) [5] and Fixed Point Continuation (FPC) [6]. However, by far the best algorithm in terms of speed and accuracy is the Split Bregman based Singular Value Shrinkage (SVS) [7].

III. HARDWARE DESIGN FOR ANALOG-TO-INFORMATION CONVERTER

The architecture of AIC based acquisition is shown in Fig. 2(b). The AIC repeatedly takes M random samples of the input signal which are digitized with a low power ADC. The input signal is then reconstructed using Kronecker Compressed Sensing (KCS). We effectively replace the Nyquist sampling SAR ADC with SAR ADC and pseudorandom clock generator to provide random under-sampling of the input signal [8]. This reduces the power consumption of the signal acquisition process and relaxes the requirements of the ADC [9]. We also no longer need to compress the data from the ADC since it will be directly compressed by the AIC at a rate of N/M compared to Nyquist. The pseudorandom clock signal is generated by Linear Feedback Shift Register (LFSR). If the pseudorandom sequence is generated completely randomly, then the maximum sample rate of the ADC must be equal to at least the Nyquist rate. We can relax the ADC requirements by restricting the minimum sample spacing. This allows the full benefits of the compressed sensing architecture, mainly a reduction in sample rate or an increased instantaneous bandwidth, to be realized even when the additional pseudorandom clock generator is taken into account. The pseudorandom clock sequence used to randomly sample the input signal will have a large effect on both the reconstruction performance as well as the overall efficiency of the AIC when implemented in hardware. Medical monitoring is an emerging application area that exemplifies the stringent energy constraints imposed on wireless sensor nodes and their corresponding circuits.

The power consumption (P_{sys}) of the system is given by,

$$P_{sys} = (P_{Amp} + P_{ADC} + JF_s R) \quad (4)$$

where P_{sys} is the power consumption of system from Fig. 2(a), P_{Amp} is the power consumption of instrumentation amplifier, P_{ADC} is the power consumption of ADC, F_s is the ADC sampling frequency, R the number of bits per sample and J the net transmission power per bit such that JF_sR gives the transmitter power consumption [10].

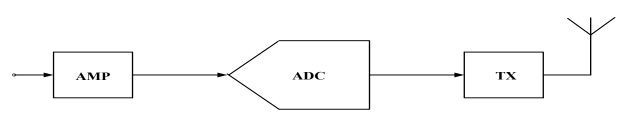

Fig. 2(a) EEG acquisition system.

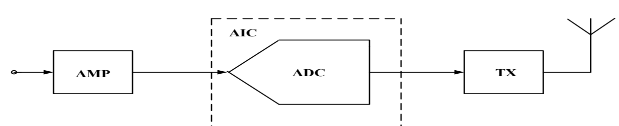

Fig. 2(b) Compressed sensing AIC based EEG acquisition system.

Compressed sensing AIC based system power consumption is now modified to,

$$P_{sys\_cs} = P_{Amp} + P_{AIC} + \frac{M}{N} JF_s R \quad (5)$$

Here the instrumentation amplifier consumption is unchanged, but one extra term representing the extra hardware required is also present: a pseudorandom clock generator (PN) is used to generate random clock sequence. In addition to this block, the power required to transmit the number of data bits (JF_sR in (4)) has been reduced by a factor of M/N.

A. *Successive Approximation Register Analog to Digital Converter*

Compressed sensing AIC consists of an SAR ADC with random sampling operation. Its low energy consumption scales linearly with the samples allowed the power efficiency of the AIC to be maximized by taking advantage of variable time between samples. To meet the requirements, we designed 12-bit SAR ADC as shown in Fig. 3. Compared to conventional Digital-to-Analog Converter (DAC) architecture, a charge redistribution DAC array internally performs the sample and hold operation. Therefore, the sample and hold block is not needed in this implementation [11]. Typically the analog building blocks like DAC and comparator consume more than 60% of the total SAR ADC power. In order to reduce the power consumed by the DAC, we have employed smaller size capacitors. To reduce the power consumption further, a dynamic latch type comparator is incorporated in the design [12]. SAR control logic containing a sequencer and a shift register [13]. It performs a binary search on the output value of comparator. The conversion process begins by sampling the input and at the end of one conversion period the output voltage of charge redistribution DAC is given by

$$V_{DAC} = -V_{IN} + V_{CM} + D_{11}\frac{V_{REF}}{2^0} + D_{10}\frac{V_{REF}}{2^1} + .. + D_1\frac{V_{REF}}{2^{11}} + D_0\frac{V_{REF}}{2^{12}} \qquad (6)$$

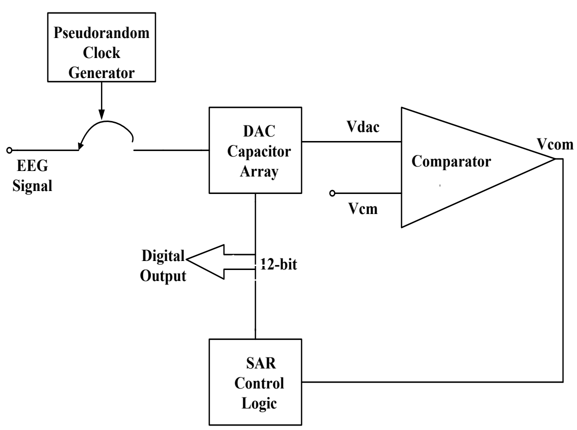

Fig. 3 Block diagram of Analog-to-Information Converter.

IV. EXPERIMENTAL AND SIMULATION EVALUATION

A. *Results of Analog to Information Converter*

The structure is designed and simulated using 65nm CMOS technology. The performance of the AIC measured at 1V supply, 0.5 KS/s. The SAR ADC is designed in single ended DAC architecture. The applied input ac signal frequency and amplitude (V_{PP}) are 200 Hz and 500 mV respectively. Timing response of the ADC is depicted in Fig. 4.

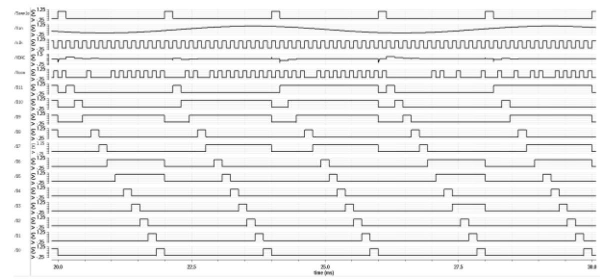

Fig. 4 Transient response of ADC.

The output spectrum for a full-scale 179.6875 Hz sinusoidal input, at a supply voltage of 1 V and sample rate of 0.5 KS/s, is shown in Fig. 5. The signal-to-noise and distortion ratio (SNDR), spurious free dynamic range (SFDR), effective number of bits (ENOB) are 59.19 dB, 66.32 dB, and 9.54 bits, respectively. The performance results of the AIC are summarized in Table I.

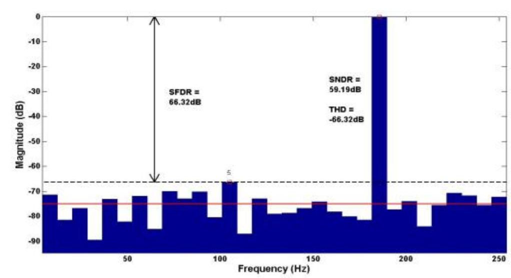

Fig. 5 AIC output spectrum.

TABLE I. AIC PERFORMANCE SUMMARY

Parameter	Value
Technology	65nm CMOS
Supply Voltage	1 V
Resolution	12 bits
Sample rate	0.5 KS/s
Power Consumption	108 nW
SFDR	66.32 dB
SNDR	59.19 dB
SNR	60.12 dB
ENOB	9.54

B. *Evaluation of Reconstruction Algorithm*

There is no actual benchmark to compare our proposed method. Previous Compressed Sensing based methods are incapable of operating in the sensing paradigm where the EEG signal samples are partially sampled. However in order to test our method, we compare it against two state-of-the-art CS based recovery schemes - sparse recovery [1] and BSBL recovery [2].

The experiments are carried out on the BCI Competition III dataset 1 [14]. We tested the recovery results for two different sub-sampling ratios - 50% (2:1) and 25% (4:1). The metric used for evaluation is the Normalized Mean Squared Error defined as $NMSE = \frac{\|original - reconstructed\|_2}{\|original\|_2}$. The reconstruction results are shown in Table II. For each signal ensemble and for each configuration, the random sampling matrix has been simulated 100 times. The mean and standard deviations (of NMSE's) for all the EEG signals in the dataset are reported.

TABLE II. COMPARATIVE RECONSTRUCTION RESULTS (NMSE) ON BCI COMPETITION III DATASET 1

Method	**Compression Ratio**	
	2:1 (mean, std)	**4:1 (mean, std)**
BSBL [2]	0.212, ±0.120	0.368, ±0.188
Sparse Reconstruction [1]	0.380, ±0.154	0.518, ±0.196
Proposed Reconstruction	0.066, ±0.028	0.102, ±0.080

Our proposed method yields significantly better reconstruction results than the previously known CS techniques [1, 2] for both under-sampling ratios.

NMSE is a well accepted measure for comparing reconstruction accuracy in CS recovery problems. However, signal reconstruction is not the end of the story. In most cases, the recovered EEG signals are analyzed by human experts or via some automated process. It is not feasible to obtain feedback from human experts on a large number of EEG signals; thus in this work we carry out an automated classification task on the BCI competition III Dataset 1 in order to see how the reconstruction has affected the performance. We carry out the classification on the original and the reconstructed signals using algorithm [15] - this is one of the competing algorithms for BCI competition. The classification results are given in the following Table.

TABLE III. CLASSIFICATION ACCURACY IN %

Method	**Classification Accuracy**	
	Compression 2:1	**Compression 4:1**
Original	81% (No Compression)	
BSBL Reconstruction [14]	73%	52%
Sparse Reconstruction [7]	70%	50%
Proposed Reconstruction	80%	60%

We find that our proposed method yields better classification accuracy than the previous CS based techniques. It is only marginally worse than the original data.

V. CONCLUSION

Current CS based techniques in energy efficient transmission of EEG signals on WBAN's can only reduce the communication costs. For the first time in this work we propose to reduce the sensing and processing energy costs as well. We achieve this by sub-sampling the EEG signals in the time domain and recovering the multi-channel signal ensemble using low-rank matrix completion techniques. We compare our proposal with previous CS based techniques. Our method yields better recovery results. Quantitative evaluation shows that the reconstruction is almost indistinguishable from the fully sampled signal. Analog-to-Information Converter implemented in 65nm CMOS technology and achieves a sample rate of 0.5 KS/s, an ENOB 9.54 bits, and consumes 108 nW from 1 V power supply.

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