Quantifying the Feasibility of Compressive Sensing in Portable Electroencephalography Systems

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Abstract. The EEG for use in augmented cognition produces large amounts of compressible data from multiple electrodes mounted on the scalp. This huge amount of data needs to be processed, stored and transmitted and consumes large amounts of power. In turn this leads to physically large EEG units with limited lifetimes which limit the ease of use, and robustness and reliability of the recording. This work investigates the suitability of compressive sensing, a recent development in compression theory, for providing online data reduction to decrease the amount of system power required. System modeling which incorporates a review of state-of-the-art EEG suitable integrated circuits shows that compressive sensing offers no benefits when using an EEG system with only a few channels. It can, however, lead to significant power savings in situations where more than approximately 20 channels are required. This result shows that the further investigation and optimization of compressive sensing algorithms for EEG data is justified.

Keywords: Compressive Sensing, Electroencephalogram, Power efficient, Wireless Systems.

1 Introduction

Augmented cognition systems which aim to close the loop on human-computer interactions intrinsically require some form of physiological monitoring of the human. The electroencephalogram (EEG), which places multiple recording electrodes on the head and records the micro-Volt sized signals produced, is a popular choice for this. The eventual level of end-user acceptance of augmented cognition technology will thus be strongly dependent on the miniaturization of the EEG technology so that it is discrete, comfortable and long-lasting. This last point is also an important factor in the design of robust systems. For example, in the dismounted solider scenario the EEG equipment may have to operate reliably over many days while the solider is out of contact with friendly forces. Also, when using EEG devices with people with learning difficulties, physically large systems requiring frequent battery changes could be a major impediment to producing reliable and repeatable results.

It has been shown [1] that power consumption, and in turn the battery size, is the major determining factor in the overall device size and system lifetime. For wireless

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EEG systems (which are potentially more discrete and wearable) most of the system power is consumed by the wireless transmitter, and thus it is desirable to compress the raw EEG data in real-time on the wearable device, in order to reduce the amount of data to transmit, and thus increase the operating lifetime or decrease the battery size.

This paper investigates applicability of compressive sensing, a recent development in compression theory, for this online data compression. An overview of compressive sensing theory is given in Section 2, but the work here assumes, based upon previous studies with EEG data [2] as well as in applications such as MRI where compressive sensing has been used very successfully [3], that compressive sensing can be used to achieve an acceptable compression ratio and reconstruction error. Instead, the focus here is on investigating the computational complexity of the method, and the implications of this for its implementation in an online, low power system.

Based upon the system modeling presented in Section 3, it is found that compressive sensing is not a beneficial compression technique when applied to an EEG system consisting of only a few channels, as commonly used in augmented cognition systems. However, as more channels are used, and many systems may commonly use 128 or more channels, the compressive sensing scheme can lead to a significant reduction in the overall power consumption. These results are presented, and the implications discussed, in Section 4.

2 Compressive Sensing Overview

The concept of compressive sensing [4] and [5] is based on the fact that there is a difference between the *rate of change* of a signal and the *rate of information* in the signal. Traditional Nyquist sampling, putting the signal into the digital domain ready for wireless transmission, is based on the former. The Nyquist theorem states that it is necessary to sample the signal at a rate at least twice the maximum rate of change present. A conventional compression algorithm would then be applied to all of these samples taken to remove any redundancy present, giving a reduced number of bits that represent the signal.

In contrast, compressive sensing exploits the information rate within a particular signal. Redundancy in the signal is removed during the sampling process itself, leading to a lower effective sampling rate. Provided certain conditions are satisfied [5], sampling at a sub-Nyquist rate the signal can still be accurately recovered.

To illustrate this, consider an EEG signal of interest $\mathbf{x}$ which is a vector of N digital samples; i.e. $x[n]$ where n =1, 2 … N. Then assume that this signal can be represented by a projection onto a different basis set:

$$x = \sum_{i=1}^{N} s_i \Psi_i \text{ or } \mathbf{x} = \mathbf{\Psi s} \tag{1}$$

where $\mathbf{s}$ is a N×1 basis function vector and $\mathbf{\Psi}$ is a N×N basis matrix. The matrix $\mathbf{s}$ can be calculated from the inner product of $\mathbf{x}$ and $\mathbf{\Psi}$:

$$s_i = \langle \mathrm{x}, \Psi_i \rangle . \tag{2}$$

For example, if $\mathbf{\Psi}$ is the Fourier basis set of complex exponential functions, **s** is the Fourier transform of **x** and both **s** and **x** represent the signal equivalently, but in different domains. In compressive sensing $\mathbf{\Psi}$ is chosen so that **s** is sparse – a vector is K-sparse if has K non-zero entries and the remaining $N–K$ entries are all zero. **s** is thus a more *compact* representation of the signal than the original **x**.

Similar to this projection, assume that **x** can be related to another signal **y**:

$$\mathbf{y} = \mathbf{\Phi x} \tag{3}$$

where **y** is a $M\times1$ vector and $\mathbf{\Phi}$ is a matrix of dimensions $M\times N$ where $M<N$. Thus:

$$\mathbf{y} = \mathbf{\Phi \Psi s}\,. \tag{4}$$

Provided that $\mathbf{\Phi}$ is correctly chosen so that no significant information is lost during the reduction in dimensionality, it is possible to use $\mathbf{\Phi}$ to sample the sparse signal **s**, rather than the original signal **x** to give an output vector **y** which has only M entries rather than the original N. If $M<N$ data compression is thus achieved, and the signal **y** would be transmitted from the portable EEG unit. It can be shown [5] that this technique is possible if $\mathbf{\Phi}$ and $\mathbf{\Psi}$ are incoherent; that is if the elements of $\mathbf{\Phi}$ and $\mathbf{\Psi}$ have low correlation.

Given a compressed measurement **y** at the receiver, the signal **x** can be reconstructed by solving the L1 problem:

$$\min_{\mathbf{s}\in\Re^N} \|\mathbf{s}\|_{\ell 1} \text{ subject to } y_i = \langle \mathbf{\Phi}_{\mathrm{i}}, \mathbf{\Psi s}\rangle \tag{5}$$

which finds the vector **s** with the lowest L1 norm that satisfies the observations made. This is then easily converted back into **x**. In general, the L1 minimization problem is non-trivial and computationally complex, but there is no need for this to run online in the portable EEG unit. The EEG signal **x** will be sampled as signal **y**, and these samples wirelessly transmitted to a base station which will then regenerate **x** from **y** offline. The fact that compressive sensing based data compression has all of its computational complexity in the backend, where power and size constraints are not as stringent is a major factor motivating its investigation.

Previous work, [2], using Gaussian Random matrices with independent and identically distributed random variables or the Bernoulli matrix as the measurement matrix $\mathbf{\Phi}$ has shown promising (although not conclusive) results on the application of compressive sensing theory to EEG signals. However, the optimal choice of N and M, which set the amount of data compression but also reconstruction error, and the choice of optimization algorithm for the reconstruction are still open questions.

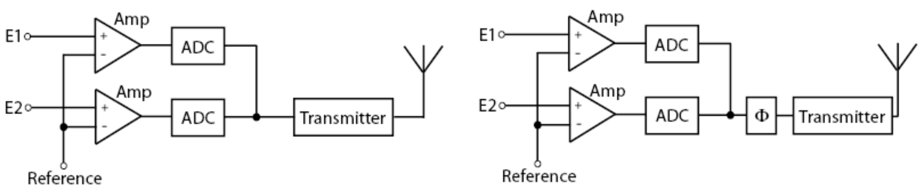
3 System Modeling and Feasibility Analysis Framework

The answering of these open questions is not the focus of this work. Before considering them it is instead essential to assess the feasibility of the overall scheme from the power point of view: the aim of compression must be to reduce the system power consumption so it is necessary to assess whether this is achievable. There is little practical point in optimizing the parameters identified above if this decrease is system power is not achievable.

An investigation of this can be carried out by considering the simplified EEG system model from Figure 1a. This incorporates an input instrumentation amplifier to amplify the small EEG signals from the head, an analogue-to-digital converter (ADC) to convert the EEG signals into the digital domain ready for transmission, and a transmitter. Given this, the system power consumption for a C channel system (P_{sys}) is given by:

$$P_{sys} = C\left(P_{Amp} + P_{ADC} + Jf_s R\right) \tag{6}$$

where P_x is the power consumption of block x from Figure 1a, 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. It is assumed that band-limiting of the EEG signal is incorporated into the instrumentation amplifier.



a) A standard EEG unit.

b) An EEG unit incorporating compressive sensing.

Fig. 1. Simplified EEG system model to enable power modeling

For comparison, Figure 1b illustrates the necessary modifications required to incorporate compressive sensing into the EEG system. The compressive sensing is implemented in the discrete domain and all that is required is a block to generate the measurement matrix $\mathbf{\Phi}$ which would be used to select a random set of samples to form $\mathbf{y}$. Elements in $\mathbf{\Phi}$ form a pseudo-random sequence following a particular probability distribution.

Given this, the system power consumption per channel (P_{sys_cs}) is now modified to:

$$P_{sys\_cs} = C\left(P_{Amp} + P_{ADC}\right) + P_{RNG} + P_{DSP} + P_{Sync} + J\left(\frac{M}{N}\cdot Cf_s R + S\right). \tag{7}$$

Here the instrumentation amplifier and ADC power consumptions are unchanged, but three extra terms representing the extra hardware required are also present: a random number generator (P_{RNG}) is used to generate the $\mathbf{\Phi}$ matrix; a DSP or microcontroller (P_{DSP}) is used to carry out the matrix multiplications from (4); and a synchronization unit (P_{Sync}) is used so that $\mathbf{\Phi}$ matrix does not need to be transmitted – it can be reconstructed at the receiver based upon the known pseudo-random sequence and a seed. Only one of each of these blocks is required regardless of the number of channels in the system. In addition to these blocks, the transmitter power consumption has changed in a number of ways.

Firstly, the power required to transmit the number of data bits (CJf_sR in (6)) has been reduced by a factor of M/N. This corresponds to the compressive sampling in (3) where there is a reduction in dimensionality between **x** and **y**. In addition, however, it is necessary to also transmit S bits of extra data corresponding to the synchronization required between the EEG unit and the receiver to regenerate the $\mathbf{\Phi}$ matrix. Again the number of bits needed does not depend on the number of channels present as the same $\mathbf{\Phi}$ matrix will be used for all channels.

To assess the feasibility of compressive sensing based systems in low power portable EEG equipment it is thus simply a matter of comparing (6) and (7) using realistic, and state-of-the-art, figures. For this, five separate blocks need to be considered. These are discussed in turn below and the end figures used, incorporating some rounding and safety factors, are summarized in Table 3.

Instrumentation amplifier. The input amplifier is responsible for amplifying the small EEG signals detected on the scalp (typically in the range 2 µV to 500 µV) so that they match the input range of the analogue-to-digital converter. In addition it is assumed that the signal is band-limited (to the approximate range 0.5 Hz to 70 Hz) in this stage. The performance of a range of state-of-the-art integrated circuit EEG amplifiers is illustrated in Table 1.

Table 1. A comparison of state-of-the-art EEG suitable instrumentation amplifiers

Reference	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Gain [dB]	40	44	77	40	44	48	38
Bandwidth [Hz]	30	1000	600	500	200	100	200
Input referred noise integrated over bandwidth [µVrms]	1.6	1.5	0.26	10	1.3	0.59	0.89
Process technology [µm]	1.5	0.35	1	3	0.35	0.5	3
Supply voltage [V]	2.5	1	5	2.5	1	3	2
Power consumption (P_{Amp}) [µW]	0.9	1.4	3,000	75	50	7	34

Analogue-to-digital converter. The ADC is responsible for digitizing the EEG ready for transmission, and the core parameter of interest is the resolution which sets the number of bits taken per sample and the end level of quantization noise. If any d.c. offset in the EEG signal is removed by the instrumentation amplifier a resolution of 10-12 bits is generally sufficient for the clinical recording of the EEG [13]. Given this, and the approximate 200 Hz sampling rate required, the performance of a selection of state-of-the-art ADCs is illustrated in Table 2. Thus, based upon Table 1 and Table 2, an overall power consumption for the instrumentation amplifier and the ADC of 2 µW is assumed to be reasonable.

Table 2. A comparison of state-of-the-art ADCs with suitable resolutions and sampling rates

Reference	[11]	[14]	[15]	[16]	[17]	[18]
Resolution (R) [bits]	11	8	12	10	10	10
Sampling rate (f_s) [kS/s]	8	1000	0.5	0.7	100	3.2
Process technology [μm]	0.5	0.18	0.18	0.8	0.09	0.5
Supply voltage [V]	3	0.6	1	2	0.65	1.2
Power consumption (P_{ADC}) [μW]	23	0.4	0.2	2.3	27	0.055

Random number generator. An example random number generator for use in generating the **Φ** matrix is given in [19], and as [19] also contains a comparison with other random number generators with respect to bit rates and power consumption, it is taken to be representative. This operates at 5V on a 0.35 μm process consuming 2.9 μW for an output data rate of 500 bps.

Processor unit for matrix multiplications. The matrix multiplications to carry out the compressive sensing will need to be implemented in either a dedicated digital signal processing chip or a microcontroller. The overall power of this depends strongly on the specifications of the model chosen for use. To be representative here, the estimates are taken based upon the popular TI MSP430 family, although possibly lower power dedicated components may be available.

In addition, the complexity of the multiplication operation depends on the size of the matrix used. In general for an $N\times N$ matrix it is an $O(N^3)$ process [20]. In the case for compressive sensing, however, where the **Φ** matrix is $M\times N$ this bound reduces to $O(M^{1.594}N)$ [21], significantly reducing the power required. Even so, based upon a **Φ** resolution of 16 bits, for any reasonable M and N it is likely that the MSP430 will have to be operated at the maximum clock frequency of 1 MHz, corresponding to an active mode power consumption of approximately 352 μW [22]. It is unlikely that portable EEG systems will be designed to have more than 64 channels, hence this power rating is considered to be the worst case scenario for systems having 64 or smaller number of channels.

Synchronization unit. For the purposes of the analysis here P_{Sync} and S are assumed to be negligible: they are essentially one time (start-up) operations that require the generation and transmission of approximately 48 bits (16 to initiate the random number process and 32 for the synchronization with the receiver). Compared to a continuous data rate in the range of kbps even for compressively sensed EEG this is deemed negligible.

Transmitter. The figure for J, the net energy per bit transmitted is simply taken from [23] which summaries the performance of several off-the-self transmitters finding that 50nJ/b is a conservative figure which should be readily achievable in most usage situations, and 5nJ/b is a more speculative figure for what may be possible. In this work this speculative 5nJ/b figure is used.

Table 3. Summary of the model parameters used and their justification

Parameter	Symbol	Value	Reasoning
Front end power	$P_{Amp} + P_{ADC}$	2 μW	From Tables 1 and 2.
Random number generator power	P_{RNG}	3 μW	From [19].
Matrix multiplication power	P_{DSP}	352 μW	From [22] and discussion above.
Seed and synchronization power	P_{Sync}	0 μW	From discussion above assumed negligible.
Transmitter energy required per bit transmitted	J	5nJ/b	From [28].
Net number of samples taken:	M	Variable	The effect of this will be investigated in Section 4.
Compressive sensing frame size:	N	750	Arbitrary choice to illustrate one performance point.
Nyquist sampling frequency	f_s	200 kS/s	From standard EEG specifications [13].
ADC sampling resolution	R	16 bits	Idealized value
Bits required to initialize random number process and synchronize with receiver	S	0 bit	From discussion above assumed negligible
Number of channels in the system	C	Variable	The effect of this will be investigated in Section 4.

4 Results and Discussion

Given the figures from Table 3 the implications of (6) and (7) can be investigated. Fig. 2 shows how the ratio M/N, which determines the amount of compression achieved as well as the end reconstruction error, affects the system power. In Fig. 2, N is arbitrarily set to 750 samples to limit the size of each matrix multiplication required. As may be expected, increasing M results in transmitting more data and so the system power consumption increases. The overall power consumption is also seen to be a strong function of the number of channels used.

This is illustrated more clearly in Fig. 3 which takes a compressive sensing operating point of M=80, N=750, and shows how the system power consumption varies with the number of channels present when compressive sensing is and isn't present. From this it is seen that for this operating point a compressive sensing based system is only feasible if more than 22 channels are to be present. When fewer channels than this are needed it is preferable to simply transmit the raw data.

This potentially has significant implications for augmented cognition applications of the EEG. For example, many augmented cognition applications such as [24] and [25] are using in the region of six channels. If this is sufficient for use there is no benefit to a compressive sensing based system, and optimizing the reconstruction performance and answering the open questions about basis functions and similar is not of practical interest at this time.

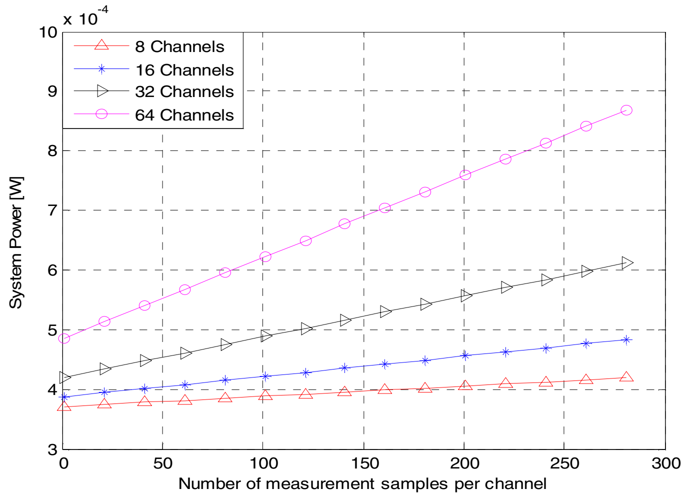


Fig. 2. The trade-off between the number of measurement samples taken (*M*), the number of channels used and the total system power consumption

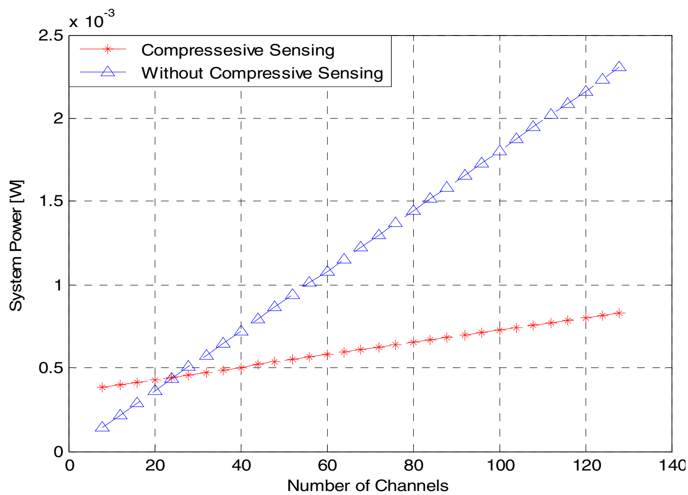


Fig. 3. The trade-off between the system power consumption and the number of channels (*C*) used for *M/N*=80/750 illustrates that a compressive sensing based system is only feasible when more than 22 channels are used

In contrast, there are other augmented cognition systems such as [26, 27] which are using 128 or more channels for recording. In this situation the use of compressive sensing is highly beneficial, with a reduction in system power consumption by 1.5mW being achievable for a 128 channel system. Using a conventional 30mWh small coin cell battery this could increase operational lifetime from 13 hours to 36 hours. In turn this can lead to significant improvements in the reliability, robustness and ease of use of systems allowing the accurate collection of physiological data.

5 Conclusions

Online data compression can be of significant use in facilitating the operation of portable EEG units from physically small batteries over a long period of time. In turn this aids the reliability and robustness of the overall system as the device is easier to use and more comfortable to wear. This paper has quantified the feasibility, from a power point of view, of using compressive sensing in order to provide this online data reduction.

Compressive sensing is a recent development in compression theory that states that it is possible to effectively sample a signal at a sub-Nyquist rate and yet still be able to accurately reconstruct the signal. Assuming that acceptable signal reconstruction is possible, this paper has presented a system modeling framework that quantifies the required power overhead for the compression system.

It was found that the feasibility of a compressive sensing based EEG system is a strong function of the number of channels present in the system; no benefit is present when less than 22 channels are needed (for the case considered here), but large power savings can be made when high numbers of channels are present. The feasibility of a compressive sensing based EEG system thus varies on an application-by-application basis, and the framework presented here can be used to assess this.

Given this result, there are potential benefits to using a compressive sensing system. Future work will thus focus on answering the many open questions still present: for example what basis functions and compression ratios can be used to minimize the reconstruction error.

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