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Design of Compressed Sensing systems for wireless sensor under the performance and reliability constraints

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Abstract: The system design of a com- pressed sensing (CS) based source encoding system for data compression in wireless sensor applications. The trade-off between the required transmission energy (compression performance) and desired recovered signal quality in the presence of practical non-idealities such as quantization noise, input signal noise and channel errors. The end-to-end system evaluation framework was designed to analyze CS performance under practical sensor settings. The evaluation shows that CS compression can enable over 10X in transmission energy savings while preserving the recovered signal quality to roughly 8 bits of precision. To present low complexity error control schemes tailored to CS that further reduce the energy costs by 4X as well as diversity scheme to protect against burst errors. Results on a real electrocardiography (EKG) signal demonstrate 10X in energy reduction and corroborate the system analysis.

Index Terms: Compressed sensing, error correction codes, source coding, wireless sensors, energy efficiency.

I. INTRODUCTION

The energy cost to wirelessly transmit data's typically orders of magnitude greater than any other function that is common within a wireless sensor. Thus, in order to address sensor lifetime it is paramount to minimize the amount of transmitted data. Consequently there have been many efforts across a variety of applications to find low-cost, low-energy data compression schemes that can be implemented locally at the sensor node. For each scheme, there is a trade-off between data reduction, information integrity, and implementation cost, where the goal is to minimize the total amount of energy required to preserve the desired information.

II. LITERATURE REVIEW

Compressive sensing established itself by now as a new sampling theory which exhibits fundamental and intriguing connections with several mathematical fields, such as probability, geometry of Banach spaces, harmonic analysis, theory of computability and information-based complexity. [1], Transient errors in an LZ encoder can propagate to cause significant corruption to the reconstructed data. Two rollback recovery schemes based on the inverse comparison CED can be used to recover the LZ encoder from such transient errors. [2],

To an information theorist, "compression" is the efficient representation of data with bits. In this article, we have looked at compressive sampling from this perspective, to see if random measurements of sparse signals provide an efficient method of representing sparse signals. [3]. WSNs provide flexible and low cost means to accurately diagnose the structural health of civil infrastructures. For this purpose, damage detection and localization represent critical tasks to be performed. Transmitting hundreds of kb of data to the sink node for off-line data analysis would quickly drain the power source of the nodes, reducing the life time of the entire System, and would consistently increase the latency [4]. Wireless sensor

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networks (WSNs) will play a key role in the extension of the smart grid towards residential premises, and enable various demand and energy management applications. Efficient demand-supply balance and reducing electricity expenses and carbon emissions will be the immediate benefits of these applications. [5]. A novel IWSN with on-sensor feature extraction and fault diagnosis and Dempster–Shafer classifier fusion. The feasibility and effectiveness of the proposed system has been demonstrated by a set of laboratory experiments on a single phase induction motor. [6].

III. PROPOSED WORK

Compressed Sensing (CS) seeks to represent a signal using a number of linear, non-adaptive measurements. Usually the number of measurements is much lower than the number of samples needed if the signal is sampled at the NY Quist rate, thus providing the benefits of reduced storage space and transmission bandwidth due to the phenomenal compression achieved. These features make CS an ideal candidate for use in wireless sensor networks (WSNs), where transmissions must be minimized in order to conserve limited power resources. Figure 1 Shows Architectural Design of proposed methodology.

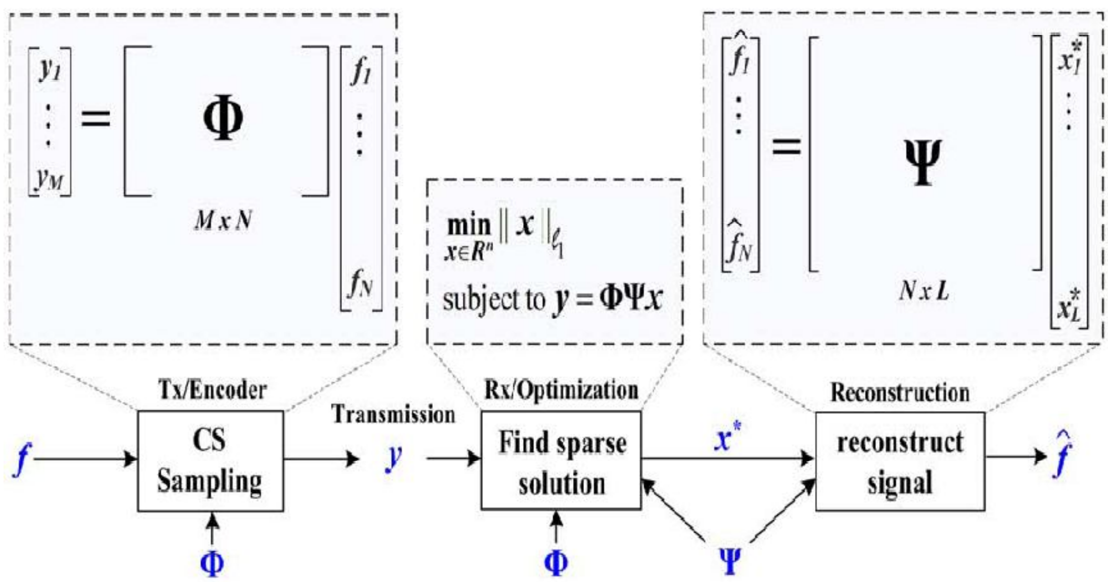

Fig 1.Architectural Design of Proposed Methodology

A.COMPRESSED SENSING BACKGROUND

CS theory first and foremost assumes that the signal of interest, , has a *sparse* representation in some basis For example, a sine wave captured in the time domain requires an infinite number of non-zero samples, whereas it only requires a single non-zero coefficient in the Fourier domain

When the signal is sparse, CS theory proposes that acquiring only a small number of compressed measurements can capture the necessary information to recover the signal. This framework where the -dimensional input signal, is directly

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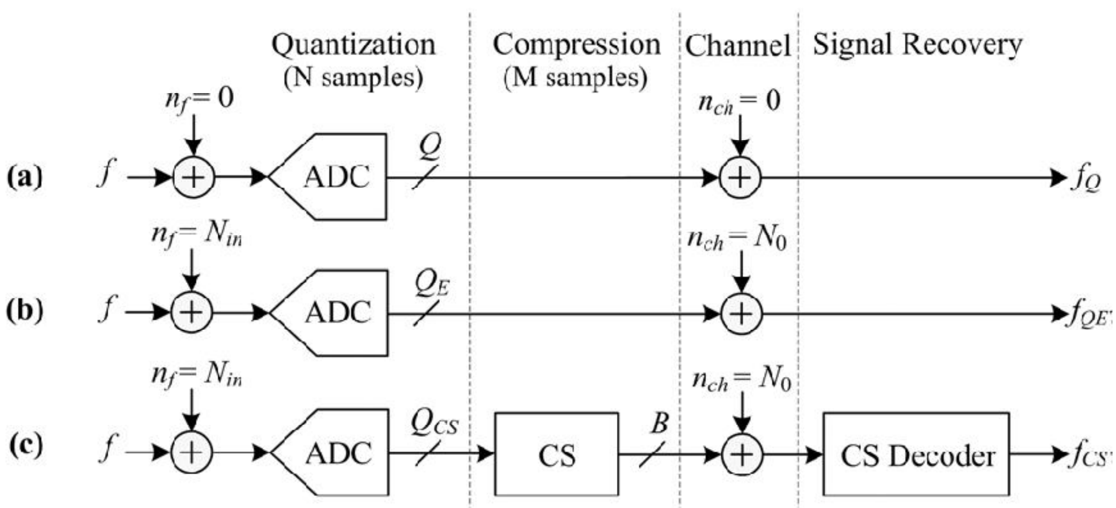
encoded into an -dimensional set of measurements via an measurement matrix . When the linear system of equations is underdetermined therefore multiple signals, may produce the same measurements, , making the problem of reconstructing from Fortunately, the sparsest solution to is often unique, and the typically intractable (NP) sparse recovery Problem is well approximated by the convex relaxation. The main point is that these reconstruction algorithms have practical implementations for estimating the sparse solution.

In signal processing, sampling is the reduction of a continuous signal to a discrete signal. A common example is the conversion of a sound wave (a continuous signal) to a sequence of samples (a discrete-time signal). A sample refers to a value or set of values at a point in time and/or space. A sampler is a subsystem or operation that extracts samples from a continuous signal.

B.EVALUATION FRAMEWORK

Since most work in CS theory is focused on determining asymptotic performance bounds, a simulation framework must be established to evaluate the performance of a practical CS-based wireless system when the block size is finite. Thus, in this section we describe a set of models and performance metrics for comparison and choose an appropriate signal test set to capture the salient characteristics of the CS algorithms.



SYSTEM MODEL AND PERFORMANCE MATRICES

Fig shows three system models chosen to highlight the main issues and challenges of designing the system. Fig. (a) Shows an idealized wireless sensor node infrastructure, which Assumes that the input signal to the ADC is noiseless, and that the quantized data is received error-free. The quantization resolution, , is chosen to meet the error requirement of the application. Since any practical system will require being finite, we treat this as the baseline performance for comparison with subsequent systems. Fig (b) Shows a more complete model that includes signal noise and channel noise. The last system model shown in Fig 3(c) includes the effects of compression with CS. Although the CS framework does not necessarily require the input to be quantized, it does require the dynamic range of the input to be preserved. So for Fig. 3(c), represents the number of bits that correspond to the input dynamic range. To compare the systems shown in we adopt the

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percent root-mean-square difference (PRD) metric, which is commonly used in quantifying information loss in biomedical signals.

C. *COST OF TRANSMISSION ERRORS*

To capture the general effect of channel errors, the wireless channel is modeled using an additive white Gaussian noise (AWGN) channel with a noise variance of and signal energy of. The bit error rate (BER) equals the Gaussian Q-function evaluated at, where SNR is the signal-to-noise ratio. Any sensor input signals that occur in practice will be somewhat noisy. To capture the effect of signal noise, white Gaussian noise is added to the system inputs of the minimum energy curves when the input noise variance. Another observation that can be drawn from is that the achievable PRD of the CS system is less limited by input noise than by quantization noise.

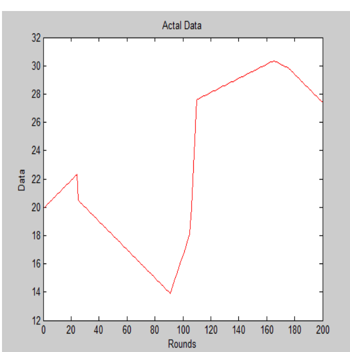
D.PROTECTION AGAINST CHANNEL NON-IDEALITIES

Thus far we have shown that CS is relatively robust to channel errors unlike typical source coding algorithms (e.g., Huffman or Lempel-Ziv) which are known to be very sensitive to transmission errors and prone to error propagation. Despite the graceful performance degradation in CS, channel coding can still further improve the energy/performance trade-off of the system. Since channel coding algorithms are typically designed without bias towards the message bits, we expect the coding performance of any existing error correction or detection schemes to work equally well with CS measurements as they do with raw quantized samples. However, since single bit errors in the measurement matrix can cause relatively large reconstruction errors, it is not necessarily clear how coding gain translates into energy efficiency.

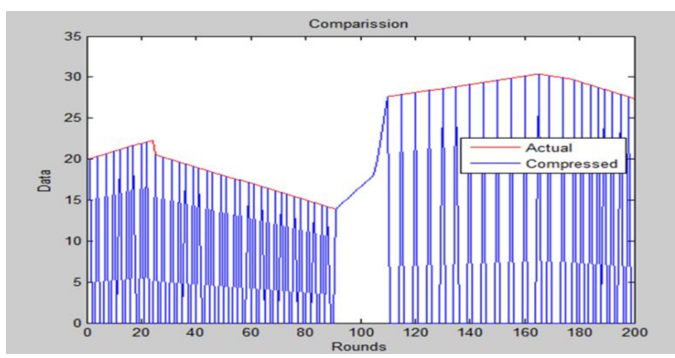
IV APPLICATIONS

We apply the analysis discussed on a real electrocardiogram (EKG) signal obtained from the MIT-BIH Arrhythmia database. For simplicity we do not consider error control schemes in this section, but simply keep in mind that the same additional energy gains described in earlier sections can be had. For this example, we are still comparing the performance of the two system models shown in only using the recorded EKG signal as the input. The recorded signals are inherently noisy so we do not artificially introduce additional signal noise (nf) .Fig. 19(a) shows a segment of the EKG signal used to conduct the experiment. To reconstruct the signal, we used an over complete dictionary of Gaussian pulses similar to the one used for the synthetic signals only with three different pulse widths. Fig. 19(b) shows a sample of the reconstructed signal for when M=100 and N=1000, resulting in a PRD of 0.5%. Additional refinement of the signal basis can be performed to improve the reconstruction error, but the results shown here are on par with the more optimized results described.

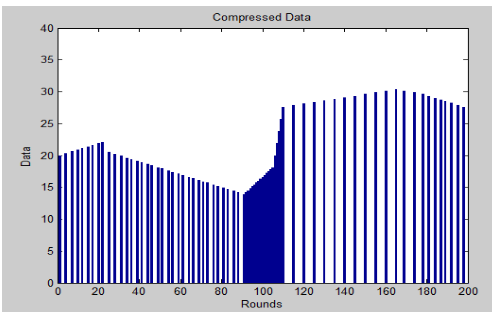
V RESULTS AND DISCUSSIONS



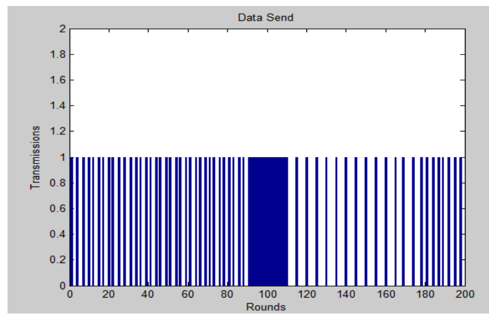
Actual data of input signal



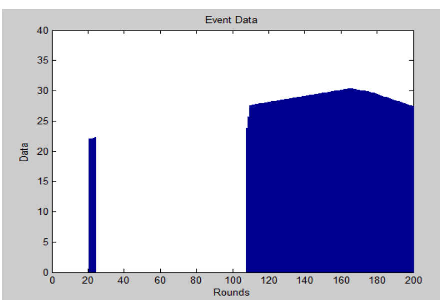
Compressed signal of Input



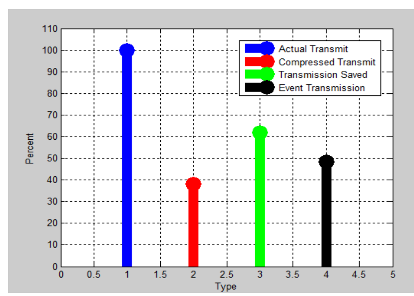
Transmission of Compressed Signal



Sampling signal



Event data Transmission



Percentage of Actual Transmit, Compressed ,Transmission Saved,Event Transmission

VI. SUMMARY AND CONCLUSION

In this work the energy-performance design space for CS, under practical constraints such as finite resolution and block lengths, it can be an efficient and robust source encoding/compression algorithm for wireless sensor applications where the signal of interest is sparse. For applications requiring modest resolution performance (bits, PRD %), CS can enable on the order of 10X reduction in transmission energy when compared to raw quantized data. CS is robust to channel errors, and is amenable to error control schemes (e.g., CRC error detection) that enable an additional 4X energy reduction and yet have simple hardware realizations. In addition to the system protocols that may be relaxed with greater error resiliency, it also proposed to a diversity scheme for CS that requires no additional transmission costs, provides greater than 10X improvement in recovered signal quality and only requires limited hardware overhead (2X). Finally the design framework and analysis presented is applicable to real world signals, such as EKGs, with a similar order of magnitude reduction in transmission energy costs.

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