Quantization Effects in an Analog-to-Information Front End in EEG Telemonitoring

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***Abstract*—Energy in wireless communication is the dominant sector of the energy consumption in electroencephalography (EEG) telemonitoring due to intrinsically high throughput. Analog-to-information conversion, i.e., compressed sensing (CS), offers a promising solution to attack this problem. Most of previous research work on CS focus on the sparse representation to reduce the signal dimension, but the impact of quantization in CS has had limited examination in the research community. In this brief, we investigate the quantization effects of CS with the application in EEG telemonitoring. In particular, we study the quantized CS (QCS) structure to explore the impacts of quantization on the performance–energy (P–E) tradeoff of the front end in EEG telemonitoring. Compared to the state-of-the-art CS with the constant bit resolution, experiments show that the QCS framework with the optimal bit resolution can improve the P–E tradeoff by more than 35%. Furthermore, the optimal bit strategy even broadens the application range of the QCS framework by 54% compared to the traditional Nyquist sampling, which indicates that the quantization is a critical factor in the entire CS framework.**

***Index Terms*—Electroencephalography (EEG) telemonitoring, optimal bit resolution, quantized compressed sensing (QCS).**

I. Introduction

ENERGY efficiency is a big challenge in the electroencephalography (EEG) telemonitoring field due to the high throughput of EEG signals [1]. Currently, wireless communication still dominates the major sector of the energy consumption and thus becomes the bottleneck of energy efficiency in EEG telemonitoring systems. To address this challenge, the emerging analog-to-information conversion, i.e., the compressed sensing (CS) technique [2], has been extensively investigated. Specifically, CS can reduce the signal sampling rate below the traditional Nyquist frequency, by exploring the intrinsic information in signals, and thus reduce the wireless communication energy consumption. Nowadays, CS has become a promising solution to reduce communication overhead and has been applied in many domains, such as physiological telemonitoring, mobile sensing, and body sensor networks.

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The state-of-the-art research work of CS mainly focuses on signal sparse representation and reconstruction. Specifically, previous work aims to select the basis to represent the signal in the sparsest manner and reconstruct the signal from the compressed low-dimensional data. In the past decade, there have been many research efforts exploring signal sparse representation and reconstruction algorithms [3]. In addition, there have been new reconstruction algorithms challenging the sparse representation assumption and obtaining good results [4]. Quantization is a necessary step in any digital signal processing scheme, and recently, there have been some research work about the relation between the quantization methods and reconstruction algorithms in CS [5]. However, to the best of our knowledge, there has been no in-depth study on how bit resolution affects the CS performance.

In this brief, we investigate the quantization effects in a CS front end. To this end, we build a parametric model of quantized CS (QCS) and analyze the quantization effects on the performance–energy (P–E) tradeoff. A case study on EEG telemonitoring indicates that the quantization strategy is critical in the CS front-end design. Experimental results show that QCS with the optimal bit resolution can improve more than 35% of the P–E tradeoff and reduce more than 28% reconstruction error compared to the state-of-the-art CS with a constant bit resolution. Moreover, the better P–E tradeoff of QCS can broaden its application range in energy by more than 50%.

The reminder of the brief is organized as follows: Section II introduces the basic CS theory. Section III describes the QCS framework in the EEG telemonitoring system. Then, the proposed parametric model of QCS to evaluate quantization effects and the optimal bit resolution strategy are explained in Section IV. Section V presents experimental results of the QCS framework for EEG telemonitoring. The conclusion and future work are summarized in Section VI.

II. Preliminary of CS

CS provides a promising analog-to-information sampling scheme. It assumes that most of meaningful signals are sparse under a certain *transformation domain*. As such, the sparse signals can be represented by a set of sparse coefficients. Moreover, many nonlinear reconstruction algorithms can efficiently estimate those sparse coefficients and accurately reconstruct the *original* signals by *inverse* domain transformation.

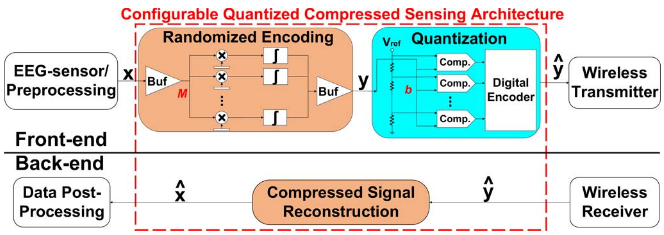


Fig. 1. EEG telemonitoring system. The red dashed rectangle indicates the QCS framework. The front end is the distributed sensor node, and the back end indicates the data center.

Given an analog input signal vector $x \in R^N$ and sensing array $\Phi \in R^{M\times N}$, we can obtain the compressed measurements $y \in R^M$ as

$$y = \Phi x. \tag{1}$$

The elements in Φ are either Gaussian random variables or Bernoulli random variables. Because of $M \ll N$, the original input signal is compressed by linear encoding. However, if only given measurements y, x cannot be resolved since the formulation in (1) is undetermined. On the other hand, input signal x is sparse under some orthogonal basis $\Psi \in R^{N\times N}$, as

$$x = \Psi u. \tag{2}$$

That is, the coefficient $u \in R^N$, under the transformation Ψ, only has few nonzero elements. Assuming that u has K nonzero elements, where $K < M < N$, u can be estimated by

$$y = \Phi\Psi u = \Theta u \tag{3}$$

where $\Theta = \Phi \times \Psi$ is an $M \times N$ array, called *measuring matrix*. The main goal of CS is to recover sparse coefficient u by measurements y. We can formulate this problem by ℓ_1 form as follows:

$$u = \min \ \|u\|_1 \quad \text{s.t.} \quad \|y - \Theta u\| < \epsilon \tag{4}$$

where ϵ is an arbitrary minimal constant. In this brief, we concentrate on the ℓ_1 convex optimization reconstruction algorithm. After solving the aforementioned formulation in (4), we can reconstruct the original input signal as follows:

$$\dot{x} = \Psi u. \tag{5}$$

III. QCS IN EEG TELEMONITORING

A. EEG Telemonitoring System

EEG is a type of important brain signal of a human being and is proved to be related with many mental disorders and diseases. The telemonitoring of EEG signals enables many applications related to brain medicine and brain–computer interface [6], such as detection and diagnosis of epileptogenesis. Fig. 1 illustrates an EEG telemonitoring system integrated in the QCS framework.

The entire system consists of two parts, i.e., front end (sensor node) and back end (data center). The sensor node is a distributed EEG body sensor gathering human vital signal in real time and sends data back to the data center. The sensor node is energy sensitive due to its limited battery capacity. After receiving the compressed data, signal reconstruction is performed, and several data analyses are carried out in the data center. The accuracy of signal reconstruction is one of the key concerns in the data center. Therefore, our focus in this brief is the quantization effects on the energy consumption in the sensor node and signal reconstruction accuracy in the data center.

In Fig. 1, the EEG sensor collects the analog raw data x. After simple preprocessing, x is sent to the randomized encoding module. The encoding module includes M branches, each of which consists of one multiplier, one row of sensing array Φ, and one integrator. The variables in the sensing array usually obey Gaussian or Bernoulli distribution. All the branches compress the analog N-dimensional raw data x into analog M-dimensional measurements y. In the quantization module, which includes b comparators and one digital encoder, compressed analog data y need to compare with the b voltages in the comparators, and then, the digital encoder outputs digital signal $\widehat{y}$ with bit resolution b based on the comparing results. The digitalized compressed data $\widehat{y}$ are sent out by wireless transmitter. When the quantized data $\widehat{y}$ arrive at the data center via wireless receiver, a sparsity-based reconstruction algorithm is applied to recover the original signal $\widehat{x}$ from the bit stream of $\widehat{y}$. Then, the reconstructed signal $\widehat{x}$ will be used for application-specific postprocessing.

B. Quantization in CS

The QCS (QCS) framework comprises three key modules, i.e., *Randomized Encoding*, *Quantization*, and *Signal Reconstruction*, within the red dashed rectangle in Fig. 1. In the QCS framework, quantization is a necessary module for digital signal transmission, due to the fact that wireless communication can only use digital signals. If given the measurements y, quantization can be implemented as

$$\widehat{y} = Q(y) \tag{6}$$

where $\widehat{y}$ is the quantized measurements, and Q is the quantization function. After a quantized data stream $\widehat{y}$ is received in the data center, the reconstruction algorithm takes quantized measurements as input, correspondingly. Therefore, the traditional ℓ_1 formulation in (4) changes to

$$\widehat{u} = \min \ \|u\|_1 \quad \text{s.t.} \quad \|\widehat{y} - \Theta u\| < \epsilon \tag{7}$$

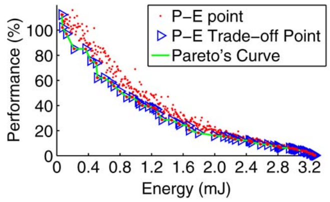
where ϵ is the noise tolerance for quantization operation. Then an accurate estimation of the original signal can be calculated as

$$\widehat{x} = \Psi\widehat{u}. \tag{8}$$

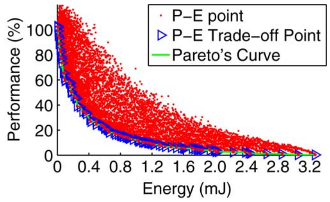
In this way, we can get the reconstructed EEG signal from the QCS framework.

IV. QUANTIZATION EFFECTS IN QCS

Here, we discuss the effects on the CS framework resulted from quantization. It leads to a new P–E model and a specific strategy for better P–E tradeoff under this new model of the QCS.



(a) Constant Bit Resolution



(b) Optimal Bit Resolution

Fig. 2. (a) Constant bit resolution ($B_C = 8$). (b) Optimal bit resolution. The red point indicates the performance on specific energy configuration. The blue triangle is the P–E tradeoff point, while the green line is Pareto's P–E curve.

A. P–E Model

Quantization is a critical part in the QCS framework. It not only affects the data accuracy for later reconstruction but also controls the transmission burden, which is an important factor in the sensor node's power consumption. In this brief, we introduce a new P–E model to quantitatively analyze the effects of quantization.

In a practical EEG telemonitoring system, energy and performance are the two most concerned factors for evaluating the entire telemonitoring system. Energy is always considered as the power consumption of the sensor node because the data center is more sensitive to the signal accuracy for postprocessing. In addition, wireless communication is the dominant part of the whole energy consumption in the sensor node [7]. Energy in communication is proportional to the total transmission bit number, involving measurements number M and quantization resolution, as

$$E \propto M \times B \tag{9}$$

where B indicates the bit resolution in the quantization. The average energy of transmitting one bit data depends on the specific implementation technology, and the energy E is proportional to M and B. For the performance, it is expected that the reconstructed EEG signal should hold the least percentage of distortion against the input EEG signal for postprocessing. In this brief, we use the normalized root-mean-square error as our performance metric. That is

$$P = \frac{\|x - \widehat{x}\|_2}{\|x\|_2} \times 100\%. \tag{10}$$

Given the definitions of performance (P) and energy (E), the P–E tradeoff point can be exploited by choosing the best performance under a certain energy constraint. When the energy constraint continuously changes, Pareto's P–E curve (optimal tradeoff curve) [8] can be found in the design space. The brute-force algorithm is a good choice to search for Pareto's curve in P–E space. Given any specific energy configuration (M, B), the corresponding performance P can be calculated. Therefore, Pareto's P–E curve can be depicted, which is the envelop curve of all the P–E points, as shown in Fig. 2.

B. Constant Bit Resolution and Optimal Bit Resolution

Bit resolution is an important but yet often ignored factor in the quantization module, which can affect both energy and performance in the QCS framework. Larger bit depth provides better quantization accuracy, which can improve the performance. However, larger bit number of a single measurement also means more energy consumption in wireless communication.

We further quantitatively investigate the quantization effects on CS by the P–E tradeoff. Specifically, traditional CS neglects the importance of bit resolution for quantization, and it always utilizes a constant value, usually 8 or 16, as the bit resolution for the CS design, which is called *Constant Bit Resolution*. Its energy formulation can be defined as

$$E_C = C \times M \times B_C \tag{11}$$

where M is the measurement dimension in the compressed domain, B_C is the constant bit resolution of quantized measurements $\widehat{y}$, and C is a constant coefficient related to wireless technology. Fig. 2(a) gives an intuitive view of the constant bit case $(B_C = 8)$ with the brute-force algorithm. From (11), we can see that there is at most one energy configuration on the same energy level. Thus, we can directly obtain its Pareto's curve by comparing the performance of every different configuration.

However, in fact, the bit resolution B can change on a certain energy level, and M changes correspondingly to maintain the energy value. This is called *Optimal Bit Resolution* strategy. We define the energy consumption of *Optimal Bit Resolution* in wireless communication as

$$E_b = C \times M \times b \tag{12}$$

where M is also the measurement dimension in the compressed domain, and b is the bit resolution of quantized measurements $\widehat{y}$. By this definition, there are several combinations of M and bit resolution b on the same energy level. Compared with the single constant bit B_C, it can provide better performance by examining all the (M, b) combinations. Given the energy level E'_b, we can calculate the performance of all the configuration combinations (M, b) on this energy level to decide which combination gives the best performance. That is

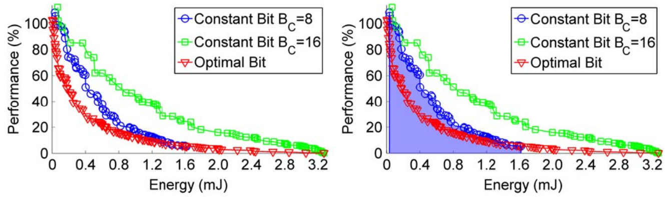
$$(M_{\text{opt}}, b_{\text{opt}}) = \arg\min_{M,b}(P) \quad \text{s.t.} \quad C \times M \times b = E'_b. \tag{13}$$

The aforementioned formulation is NP-hard, and we consider the brute-force algorithm in this problem. We can also conclude from the formulation in (13) that the constant bit is a specific combination case in our optimal bit strategy if $B_C \subset b$. Consequently, a better tradeoff between performance and energy may be found on a certain energy level. As shown in Fig. 2(b), there are more design choices of the optimal bit than the constant bit case. Optimal bit resolution clearly outperforms constant bit resolution for better P–E tradeoff.

V. Experiment and Discussion

A. Experimental Setup and Data Set

We carry out a series of experiments on the EEG signals to quantitatively demonstrate the quantization effects on CS. The first experiment is to compare constant bit and optimal bit, including P–E tradeoff and reconstructed signal quality. We also perform experiments to compare the application range of constant bit in QCS and of optimal bit in QCS and Nyquist sampling.



(a) Pareto's curves (b) AUC: Constant Bit B_C=8

Fig. 3. (a) Pareto's curves of constant bit and optimal bit. (b) Example of AUC under the constant bit case.

The main goal of EEG telemonitoring is to transmit human EEG signal to the data center for data analysis. Therefore, we use the publicly available EEG data set from the PhysioNet [9] as the test data. The signal sample is shown as the blue dashed line in Fig. 4(b)–(d). The length of EEG signal is $N = 512$, and its sampling rate is 256 Hz. All the experiments use the Gaussian random array as sensing array and the uniform quantization strategy. An inverse discrete wavelet transform is taken as our orthogonal transformation basis Ψ. All our experiments are carried out by MATLAB, with a 3.4-GHz Intel Core i7 and 8-G memory.

We adopt the IPv6-based communication model over Bluetooth low energy (BLE) on real devices [10] to model the energy consumption of wireless data transmission. The throughput of EEG signal is 0.5 kB/s, and the 512-length segment can be transmitted in one packet. Thus, according to the experiment of the connection mode of BLE, the energy consumption of this setup is 325 kB/J, i.e., $C = 0.4\ \mu\text{J/bit}$ in the energy model.

B. Optimal Bit Versus Constant Bit in QCS

1) P–E Tradeoff: This experiment aims to compare Pareto's P–E curves of the constant bit and the optimal bit in QCS. Specifically, we set constant bit $B_C = 8$ and 16, respectively, and M ranges from 10 to 512. For the optimal bit case, the range of b is between 1 and 16. M and Ψ are both the same with the constant bit case. We perform the brute-force algorithm, and all these Pareto's curves are illustrated in Fig. 3(a).

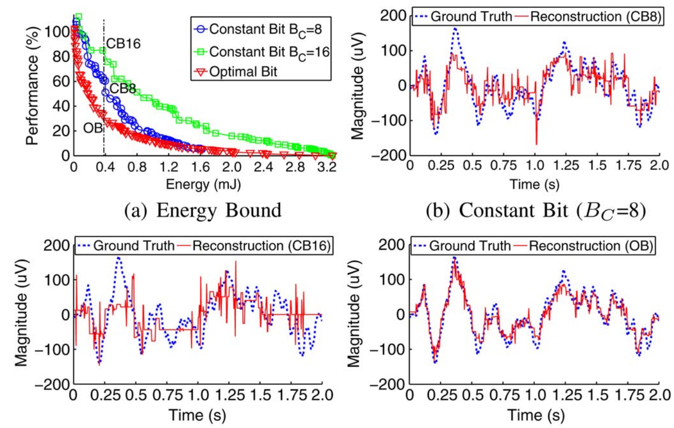
For an intuitive view, Pareto's P–E curve of the optimal bit is obviously superior to the constant cases. As energy increases, the constant bit cases gradually approximate to Pareto's P–E curve of the optimal bit. Specifically, we introduce a quantitative way to compare Pareto's curves. We employ the area under curve (AUC) [11] of the P–E curve as the evaluation criterion. AUC indicates the area between Pareto's curve and the energy axis. That is

$$AUC = \sum S_i \tag{14}$$

where i is the P–E point number, S_i is the trapezoidal area between two adjacent P–E tradeoff points and the energy axis. For example, the whole AUC of $B_C = 8$ under the constant bit is shown as the blue area in Fig. 3(b). Because the constant bit (8 or 16) just takes up an energy interval, we separately calculate AUC of the optimal bit in the same energy interval as the specific constant bit case to do the comparison, which is referred to as OB-B8 or OB-B16. Related AUC values are shown in Table I. We can use the following metric to evaluate the tradeoff enhancement:

TABLE I
AUC VALUES OF CONSTANT BIT AND OPTIMAL BIT

AUC	B_C=8	B_C=16
Constant Bit	405.2	779.9
Optimal Bit	258.4	269.9
$TOF_{enhance}$	**36.2%**	**65.4%**



(a) Energy Bound (b) Constant Bit (B_C=8)

(c) Constant Bit (B_C=16) (d) Optimal Bit

Fig. 4. (a) Energy bound $E = 0.38$ mJ on three Pareto's curves. (b)–(d) Recovered EEG signal of three cases.

$$TOF_{\text{enhance}} = \frac{AUC(CB) - AUC(OB)}{AUC(CB)} \tag{15}$$

where $AUC(CB)$ is the area of Pareto's P–E curve of the constant bit. We can see that the optimal bit can achieve a higher tradeoff of 36.2% than the constant bit $B_C = 8$ and a tradeoff of 65.4% than the constant bit $B_C = 16$. Therefore, our optimal bit strategy leads to a much better P–E tradeoff than the constant bit resolution.

2) Signal Quality: We take a closer look at the accuracy of the reconstructed results of the constant bit and the optimal bit. In this experiment, we set an energy upper bound, such as 0.38 mJ, to examine the reconstruction results, as the black dotted line in Fig. 4(a). Since P–E tradeoff points distribute on some discrete energy levels, it is possible that there is no P–E tradeoff point locating at the energy bound. Under this circumstance, we seek for the nearest tradeoff point at a less energy level than the bound. Once the energy bound is set, we can obtain three P–E tradeoff points, i.e., CB8, CB16, and OB, whose reconstruction results are shown in Fig. 4(b)–(d), respectively.

We can observe that the optimal bit resolution gives the results with the least distortion from an intuitive view in Fig. 4. Its reconstruction waveform can directly reflect all the characters of the ground truth, except some subtle details. For the constant bit resolution, the result of $B_C = 8$ can basically fit the ground truth, with some distortion. In addition, the reconstructed EEG signal of $B_C = 16$ is the worst case, which suffers from very large signal distortion from the ground truth.

The energy configuration and performance of the three tradeoff points are listed in Table II. In contrast with constant bit, the reconstruction error rate of the optimal bit is only

TABLE II
ENERGY CONFIGURATION AND PERFORMANCE ON $E = 0.38$ mJ

Trade-off Point	CB8	CB16	OB
b	8	16	4
M	117	57	229
Energy (mJ)	**0.374**	**0.365**	**0.366**
Performance	**61.06%**	**85.08%**	**33.04%**

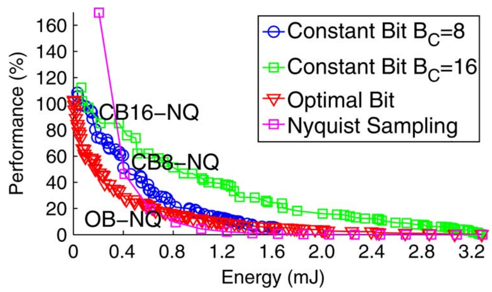


Fig. 5. Pareto's curve comparison between QCS and Nyquist sampling.

TABLE III
ENERGY CONFIGURATION OF QCS'S TURNING POINTS

Turning-Point	CB8-NQ	CB16-NQ	OB-NQ
b	8	16	6
M	117	34	241
Energy (mJ)	0.374	0.218	0.578
$ER_{enhance}$	**54.5%**	**165.8%**	-

33.04%, which is almost one times less than the constant bit. Its energy consumption is 0.366 mJ, which is almost the same with constant bit cases. Clearly, the optimal bit resolution achieves better tradeoff and better performance with similar energy consumption.

C. QCS Versus Nyquist Sampling

This experiment is designed to compare the tradeoffs of the following methods: Nyquist sampling, QCS with the constant bit, and QCS with the optimal bit, which is an indication of the application range of the specific method. The results of the P–E curve of Nyquist sampling, using the input EEG signal with the uniform quantization scheme, are shown in Fig. 5.

We can observe that the QCS framework offers better tradeoff when energy consumption is in a lower level. As energy increases, Nyquist sampling provides better P–E tradeoff. This is because ℓ_1 convex optimization can limit the quantization error, which decreases as energy grows. When it is small enough, most of the overall error stems from ℓ_1 convex optimization. With the previous results, three turning points between Nyquist sampling and two QCS cases can be obtained in Fig. 5, which are CB8-NQ, CB16-NQ, and OB-NQ. Their energy configurations are listed in Table III. In general, when the energy bound is less than the turning point, QCS offers better P–E tradeoff. On the contrary, Nyquist sampling is the better choice. Therefore, it is clear that QCS with optimal bit can greatly broaden the energy range of QCS framework application. We define ER_{enhance} as energy range enhancement. That is

$$ER_{\text{enhance}} = \frac{E_{\text{ce}}(OB) - E_{\text{ce}}(CB)}{E_{\text{ce}}(CB)} \tag{16}$$

where E_{ce} refers to the turning point energy. We can see that the optimal bit case enlarges 54.5% energy range than the constant bit $B_C = 8$ and enlarges 165.8% energy range than the constant bit $B_C = 16$. Therefore, in order to obtain better P–E tradeoff, the optimal bit strategy can greatly extend the energy range of QCS framework application.

VI. CONCLUSION AND FUTURE WORK

In this brief, we have studied the quantization effects on a CS-based front end in EEG telemonitoring. The QCS architecture with the optimal bit strategy has been proved to provide a better P–E tradeoff. In addition, we have validated the quantization effects through real EEG signals. Experimental results demonstrated that QCS with the optimal bit can effectively save energy while reducing the reconstruction error. More importantly, the QCS with the optimal bit can significantly enlarge the energy range of CS and, thus, enables wider applications.

There are many potential future works along this research topic. For example, we will investigate the optimal parameter reconfiguration dynamically, including the sampling rate and the bit resolution in quantization, for different biosignal segments. We will also explore other nonsparse representation reconstruction algorithms, such as block sparse Bayesian learning, to pursue further P–E tradeoff optimization in practice.

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