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Energy-efficient Compressed Sensing for ambulatory ECG monitoring

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ABSTRACT

Advances in Compressed Sensing (CS) are enabling promising low-energy implementation solutions for wireless Body Area Networks (BAN). While studies demonstrate the potential of CS in terms of overall energy efficiency compared to state-of-the-art lossy compression techniques, the performance of CS remains limited. The aim of this study is to improve the performance of CS-based compression for electrocardiogram (ECG) signals. This paper proposes a CS architecture that combines a novel redundancy removal scheme with quantization and Huffman entropy coding to effectively extend the Compression Ratio (CR). Reconstruction is performed using overcomplete sparse dictionaries created with Dictionary Learning (DL) techniques to exploit the highly structured nature of ECG signals. Performance of the proposed CS implementation is evaluated by analyzing energy-based distortion metrics and diagnostic metrics including QRS beat-detection accuracy across a range of CRs. The proposed CS approach offers superior performance to the most recent state-of-the-art CS implementations in terms of signal reconstruction quality across all CRs tested. Furthermore, QRS detection accuracy of the technique is compared with the well-known lossy Set Partitioning in Hierarchical Trees (SPIHT) compression technique. The proposed CS approach outperforms SPIHT in terms of achievable CR, using the area under the receiver operator characteristic (ROC) curve (AUC). For an application where a minimum AUC performance threshold of 0.9 is required, the proposed technique extends the CR from 64.6 to 90.45 compared with SPIHT, ensuring a 40% saving on wireless transmission costs. Therefore, the results highlight the potential of the proposed technique for ECG computer-aided diagnostic systems.
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1. Introduction

Modern healthcare systems may be revolutionized by the deployment of wireless Body Area Networks (BANs) [1,2]. BANs offer real-time remote monitoring of bioelectric signals such as an electrocardiogram (ECG) using wirelessly-enabled sensors. The ultimate goal of pervasive healthcare for BAN implementations faces many challenges including device size, cost and computational performance. However, the most significant challenge, that to some degree impacts on all of the others, is minimizing system power consumption. Studies have demonstrated that the main consumer of energy in ambulatory environments is wireless data transmission [3,4]. Therefore, to improve the energy efficiency of BANs, it is essential that a data reduction process is efficiently implemented to limit the impact of the power hungry wireless transmission operation. In order to reduce this RF transmission power, lossy compression is increasingly being proposed for deployment in BANs.

Compressed Sensing (CS) has recently emerged [5–8] as a low power substitute for traditional Nyquist-based lossy compression techniques such as Set Partitioning In Hierarchical Trees (SPIHT) [9]. CS computes a linear projection of a sparse signal with a random sensing matrix forming a small number of compressed samples prior to wireless transmission. Signal recovery then exploits a sparse representation of the signal in the time domain or according to a certain dictionary. This sub-Nyquist sensing removes the requirement for explicit digital signal compression, as sampling and compressing are simultaneously performed. As a result of such an efficient sampling operation, recent research has demonstrated the clear potential of CS for mobile, wearable and low power systems [10–12]. Mamaghanian et al. have shown it to be more energy-efficient than Discrete Wavelet Transform (DWT) compression for ambulatory ECG compression [10]. Mamaghanian et al. also recently proposed a CS analog front end architecture [11] that consumes 43% less power when tested on ECG signals than an ADC sampling at the Nyquist rate, further strengthening the case for CS.

Despite the significant progress made with CS, performance remains limited in terms of distortion for a given Compression Ratio (CR). This paper attempts to improve the performance of CS-based ECG signal compression, by proposing a novel CS technique

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incorporating a new redundancy removal module (to remove the redundancy inherent in ECG signals), low bit level quantization and Huffman encoding for signal acquisition. Additionally, the use of overcomplete patient-specific dictionaries are employed for signal recovery. The analysis encompasses both signal reconstruction quality and performance in the diagnostically-relevant task of QRS detection.

The principal contributions of this paper are as follows:

- A novel method of removing redundancy present in ECG signals - Redundancy Removal with Mean (RRM). The proposed algorithm performs quantization prior to the RRM operation at previously untested low bit levels and these techniques are combined with the use of highly overcomplete dictionaries created with Dictionary Learning (DL) for signal reconstruction.
- The proposed CS architecture (RRM-DL) offers superior performance in terms of signal reconstruction quality to all current state-of-the-art CS implementations in the literature.
- The paper presents a novel comparative analysis between CS and SPIHT in terms of diagnostically-relevant performance based on QRS detection. Crucially, the proposed RRM-DL CS implementation provides superior performance to SPIHT in terms of area under the receiver operator characteristic (ROC) curve (AUC) at all CRs.

The remainder of the paper is structured as follows. Section 2 describes CS and the current state-of-the-art in CS-based ECG compression. Section 3 presents the proposed CS implementation. The experimental results are in Section 4, analyzing signal reconstruction error and considering the accuracy of QRS complex extraction. Finally, Section 5 discusses practical considerations of the RRM-DL method and assesses the experimental results while Section 6 concludes the paper.

2. Compressed Sensing

2.1. Signal acquisition

The signal acquisition process of CS can be defined by (1).

$$[Y]_{M,1} = [\Phi]_{M,N}[X]_{N,1} \tag{1}$$

where X the original signal of length N and Y is the compressed signal of length M ($M \ll N$) a linear projection of X by the $M \times N$ *sensing* matrix Φ. Typically, Φ has entries which are independently identically distributed (i.i.d). Alternatively, the use of sparse binary sensing matrices, which only contain a small number of non-zero elements in each column for efficient hardware computation, were proposed in [10] and further implemented in [13–15]. However, Polania et al. concluded in [13], whilst acknowledging the potential of the sparse binary matrices, that Bernoulli distributed sensing matrices outperform the sparse binary sensing matrices in terms of signal reconstruction quality. Therefore, in these experiments, the sensing matrix entries are Bernoulli distributed ± 1 entries.

2.2. Sparse signal recovery

In order to reconstruct the original signal, a fundamental requirement of CS is that the signal can be represented by a sparse vector α, where α is a sparse representation of the reconstructed signal X' in a dictionary Ψ, as in (2). The sparse dictionary is not necessarily a square matrix and the number of columns P can be increased above N to create overcomplete dictionaries, which can enhance signal sparsity [16].

$$[X']_{N,1} = [\Psi]_{N,P}[\alpha]_{P,1} \tag{2}$$

where X' is the reconstructed signal of length N, the reconstruction dictionary Ψ ($N \times P$) contains P atoms and α is the sparse vector of length P, dependent on the dictionary size. Thus, the aim of signal recovery is to produce a sparse version of the vector α (of length P) from the vector Y (of length M). The equation for Y can then be expanded, as in (3):

$$[Y]_{M,1} = [\Phi]_{M,N}[\Psi]_{N,P}[\alpha]_{P,1} \tag{3}$$

The underlying theory behind CS states that, if the signal is sparse in the dictionary Ψ, the probability of solving the undetermined set of linear equations in (3) is high [5–7]. There are also two important conditions that the sensing matrix Φ must satisfy to ensure accuracy and robustness in signal recovery: mutual coherence with the sparse dictionary [8] and the restricted isometry property [17]. Once these properties are satisfied, CS ensures with high probability, sparse recovery of the signal from the linear measurements Y by solving the optimization problem described by (4).

$$Min\|\alpha\|_1 \text{ subject\textbackslash to } Y = \Phi\Psi\alpha \tag{4}$$

The most common method for CS recovery is l_1 norm minimization, where the vector with the minimum l_1 norm will correspond to a close approximation of the sparse representation of X, provided that enough measurements M have been taken. Alternative approaches to l_1 norm minimization include greedy algorithms such as the Orthogonal Matching Pursuit (OMP) [18] and Compressive Sampling Matching Pursuit (CoSAMP) [19], Bayesian Learning [20] and l_p pseudo norm minimization [21]. Based on the l_1 norm minimization described in (4), a reconstructed version of X can then be recovered using (2). For these experiments, the standard Basis Pursuit (BP) algorithm [22], as implemented in [23], was employed to solve Eq. (4).

2.3. CS-based ECG implementations

2.3.1. CS acquisition methods

The application of CS to ECG compression has seen increased interest in recent years. Mamaghanian et al. [10] proposed a redundancy removal technique to eliminate the significant redundancy inherent in adjacent compressed ECG measurements. The redundancy removal operation (which will be referred to henceforth as Standard Redundancy Removal (SRR)) focuses on the minimal variance of the compressed measurements of consecutive ECG frames due to a fixed sensing matrix being used and the pseudo-periodic nature of ECG signals. The approach computes the difference between consecutive measurements and performs Huffman coding on the difference, providing significant compression gains. The reported results demonstrate CS to be more energy efficient than a DWT-based compression algorithm for a given CR. However, reconstruction with a Daubechies wavelet basis resulted in their CS implementation being outperformed by the DWT-based compression algorithm from a signal reconstruction quality perspective.

2.3.2. CS reconstruction implementations

The use of a wavelet basis to create sparse representations of ECG signals has been commonly employed with CS [10,24–28]. However, the results have generally proven unsatisfactory, and consequently many alternative approaches to CS reconstruction have been explored in the literature. Pant et al. proposed an algorithm to minimize the l_p pseudo norm of the second-order difference of ECG signals [29]. The technique then utilizes patient-specific dictionaries to optimize the reconstruction quality of the l_p

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