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Multi-channel ECG data compression using compressed sensing in eigenspace

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ABSTRACT

In recent years, compressed sensing (CS) has emerged as a potential alternative to traditional data compression techniques for resource-constrained telemonitoring applications. In the present work, a CS framework of data reduction is proposed for multi-channel electrocardiogram (MECG) signals in eigenspace. The sparsity of dimension-reduced eigenspace MECG signals is exploited to apply CS. First, principal component analysis (PCA) is applied over the MECG data to retain diagnostically important ECG features in a few principal eigenspace signals based on maximum variance. Then, the significant eigenspace signals are randomly projected over a sparse binary sensing matrix to obtain the reduced dimension compressive measurement vectors. The compressed measurements are quantized using a uniform quantizer and encoded by a lossless Huffman encoder. The signal recovery is carried out by an orthogonal matching pursuit (OMP) algorithm. The proposed method is evaluated on the MECG signals from PTB and CSE multilead measurement library databases. The average value of percentage root mean square difference (PRD) across the PTB database is found to be 5.24% at a compression ratio $(CR) = 17.76$ in Lead $V3$ of PTB database. The visual signal quality of the reconstructed MECG signals is validated through mean opinion score (MOS), found to be 6.66%, which implies *very good* quality signal reconstruction.

1. Introduction

The process of depolarization and re-polarization of the atria and the ventricles leads to the generation of P-wave, QRS-complex, ST-segment and T-wave of an electrocardiogram (ECG) signal. These ECG components carry important diagnostic information about various cardiac activities and make ECG an important non-invasive diagnostic tool for heart abnormalities. The ECG data acquisition using standardized system of 12-channels is marked as Lead-I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6, and it is termed as multilead or multi-channel ECG (MECG). The MECG signals play an essential role in the detailed diagnosis of cardiac diseases [1]. The MECG signal acquisition in continuous telemonitoring applications generates large amounts of data. Since these are resource-constrained applications with limited power and bandwidth, wireless transmission of such a large amount of data to healthcare centers is very expensive. This necessitates efficient data reduction before transmission. Due to its simple and power-efficient data reduction ability, compressed sensing (CS) [2] has emerged as a potential alternative to traditional wavelet-based compression techniques [3–5], which suffer from high encoding costs [6]. CS enables the recovery of sparse signals from a small number of linear projections (called *measurements*). CS has found wide applications in many engineering fields like image and video processing [7], communication [8], etc. For biomedical signals, CS has been applied in a data compression framework for wireless telemonitoring applications [6,9–14]. A detailed review on heart monitoring can be found in [15].

Earlier CS-based works have exploited the sparse behavior of ECG signals either in the time-domain or in transform domain with wavelets as the sparsifying bases [6,9,11,12,16]. Mamaghanian et al. [6] have proposed a CS-based data compression of ECG signals for wireless body sensor networks (WBSN). Zhang et al. [9] proposed a monitoring system for fetal-ECG signals employing a block sparse Bayesian learning approach. Recently, prior knowledge-based CS recovery algorithms have been reported for ECG signals [11,12]. However, all the above works are limited to single-channel ECG signals. This has motivated us to investigate the CS framework for MECG signals. The MECGs are preferred over single-channel ECG by cardiologists due to their detailed clinical information contents [1]. There exists shared information across

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different channels in MECG signals [17,18]. The source of this common information is the electrical heart vector whose projections in different directions lead to ECG signals in different channels. To exploit this, a joint sparsity-based CS approach in wavelet domain is proposed in [18]. Another similar approach is reported in [19], which exploits the joint sparsity among the highly correlated heart-beats of single-channel ECG signals to achieve data compression. But, joint sparsity-based approaches do not deliver favorable results and end up with high output distortions and low compression efficiency. This is because, each lead conveys some unique information about the heart and hence, ECG signals from all the channels cannot be accurately represented using the same set of wavelet bases.

Principal component analysis (PCA) has been previously used as a dimensionality reduction tool to achieve MECG data compression [20]. It has also been employed to synthesize 12-channel MECG system using reduced 3-lead system for remote health monitoring applications [21–23]. The data-adaptive transformation feature of PCA makes it a good sparsifying basis for CS-based applications [8,24]. It was used jointly with CS for distributed signals to learn optimal transformation through online estimation of the signal statistics [8]. For synthetic aperture radar (SAR) signals, it has been used as a sparsifying transform to compressively measure the SAR raw data [24]. Joint PCA-CS feasibility in above applications motivated us to explore PCA in the CS framework for MECG signals. It helps capture the diagnostic information spread across 12-channels to few eigenspace signals (reduced leads) by exploiting the inter-channel correlation structure of the MECG signals. The retained PCA transformed eigenspace MECG signals can be compressively measured using CS exploiting their sparsity either in eigenspace itself or in any other transform domain. So, processing the ECG signals from different channels jointly through PCA helps exploit the spatial correlation across the channels and removes the redundant information while producing sparse eigenspace signals. This feature is generally ignored in other CS-based works that deal with each channel individually [6,11,12,19]. Power-efficient data reduction framework of CS is then applied over eigenspace signals to obtain improved joint compression of the MECG data. However, this framework requires covariance matrix of the data during the reconstruction. Noting the small size of covariance matrix (8×8, if 8 independent MECG channels are considered), it can be sent as the side information along with the data with a little effect on the resource cost of the system. After PCA transformation, the transformed eigenspace MECG signals retain a morphological similarity with the time-domain ECG signals (refer to Fig. 1), and thus, still contain intra-signal correlated structure. This correlation can be further exploited in addition to the inter-channel correlation by choosing a suitable sparsifying basis during CS reconstruction in the proposed eigenspace CS approach. It can sparsify eigenspace signals and the required number of compressed measurements can thus be further reduced. Reduced number of measurements directly translates into higher compression efficiency of the system without sacrificing the clinical quality of the reconstructed ECG signals. Different transforms, such as discrete wavelet transform (DWT), discrete cosine transform (DCT), and discrete Fourier transform (DFT), have been studied as the sparsifying bases for eigenspace signals, and CS performance is analyzed in each domain. CS reconstruction is

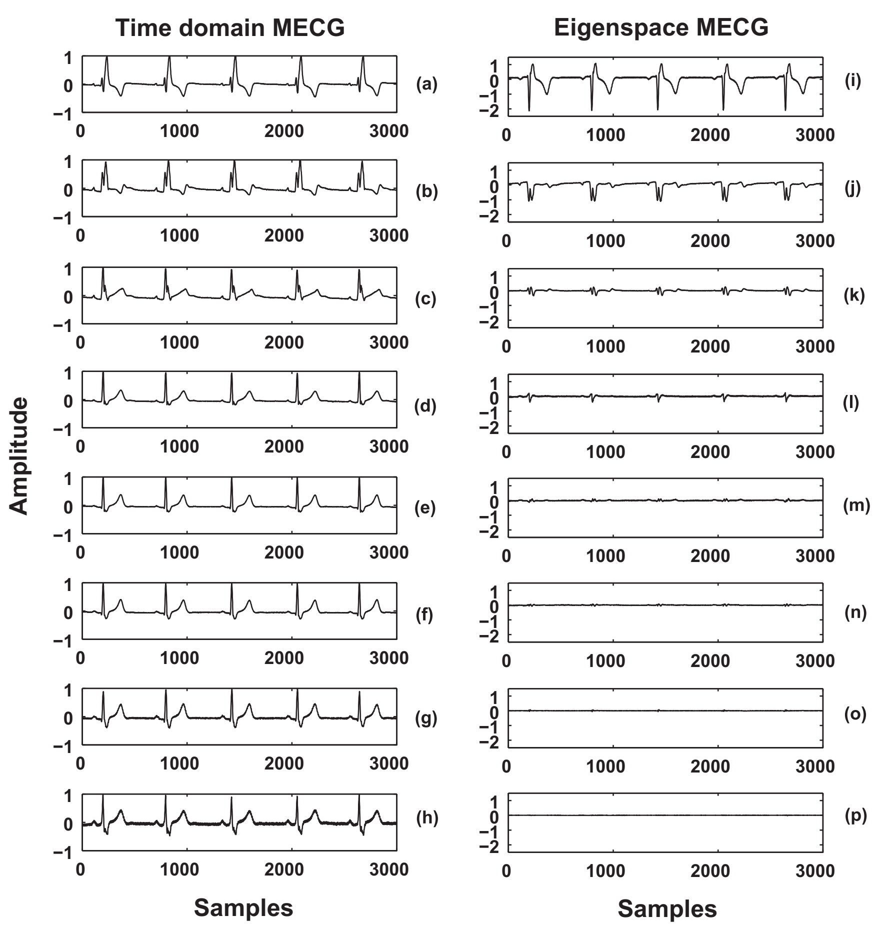

Fig. 1. Time-domain MECG signals from eight independent channels: Lead I, II, V1, V2, V3, V4, V5, V6 are shown in plots (a)–(h) respectively. PCA transformed eigenspace MECG signals from (i)–(p).