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Exploiting multi-scale signal information in joint compressed sensing recovery of multi-channel ECG signals

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Computational complexity and power consumption are prominent issues in wireless telemonitoring applications involving physiological signals. Compressed sensing (CS) has emerged as a promising framework to address these challenges because of its energy-efficient data reduction procedure. In this work, a CS-based approach is studied for joint compression/reconstruction of multi-channel electrocardiogram (MECG) signals. The MECG signals share spatially correlated cardiac information across the channels, which is exploited in a joint CS framework for improved signal recovery. Weighted mixed-norm minimization (WMNM)-based joint sparse recovery algorithms are proposed, which can successfully recover the signals from all the channels simultaneously by utilizing the joint sparsity of MECG signals in wavelet domain. The proposed algorithms exploit multi-scale signal information through a multi-scale weighting approach. Under this strategy, weights are designed based on the diagnostic information contents of each wavelet subband/scale. In particular, clinically relevant information is captured in the form of subband energy, entropy, and amplitude decay, and based on this weighting rules are defined at each wavelet scale. Such a weighting approach emphasizes nonzero wavelet coefficients having high diagnostic importance during joint CS reconstruction. Insignificant coefficients are deemphasized simultaneously, resulting in a sparser solution. Simulation results using Physikalisch-Technische Bundesanstalt (PTB), Common Standards for Electrocardiography (CSE) and Massachusetts Institute of Technology-Boston's Beth Israel Hospital (MIT-BIH) MECG databases show that the proposed methods can achieve superior reconstruction quality with a lower number of measurements compared to their non-weighted counterpart and other existing CS-based methods. Reduction in the required number of measurements reduces computational burden and directly translates into higher compression efficiency, resulting in low energy consumption in CS-based telemonitoring systems. The diagnostic reconstruction quality of the algorithm is validated using diagnostic distortion measures like wavelet energy-based diagnostic distortion (*WEDD*) and with a post-reconstruction classification task. It achieves a classification accuracy of 73.2% even when MECG signals are jointly reconstructed using only about 10% of compressed measurements, validating the diagnosability of the reconstructed signals even at very low data rates.

1. Introduction

Compressed sensing (CS) is a signal processing technique that enables signal reconstruction from a small set of linear projections, called *measurements*, provided the signal is sparse in some domain [1]. CS exploits the signal structure and enables data acquisition at sub-Nyquist rate, outputting directly the compressed form of the signal. Consequently, the signal encoding becomes quite simple and energy-efficient in the CS framework. This feature of CS motivated its use in many resource-constrained applications [2,3]. Wireless body area network (WBAN)-enabled electrocardiogram (ECG) telemonitoring is one such prominent application, where CS has been successfully used to lower the on-chip computations, energy consumption, and complexity of the system [4]. A typical block diagram of a CS-based telemonitoring system is shown in Fig. 1. The figure illustrates a digital paradigm of CS, called 'digital CS' [4], where a simple matrix-vector multiplication after analog to digital conversion (ADC) gives the compressed form of the physiological signal $\boldsymbol{x}$. The reduced dimension vector $\boldsymbol{y}$ also called the compressed measurement vector, is sent to the remote terminals (Hospitals/Health care centers) through the wireless links, where the original signal is

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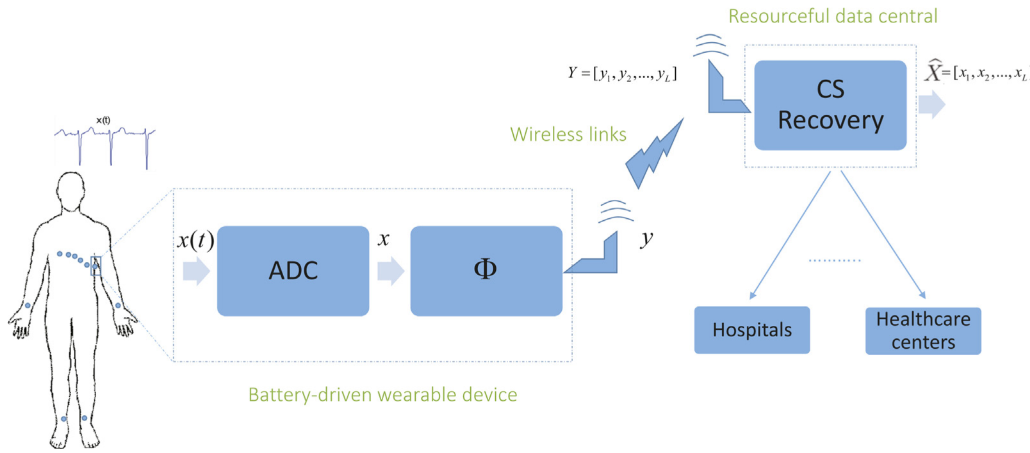

Fig. 1. A typical compressed sensing-based wireless telemonitoring system.

reconstructed using CS-based recovery techniques and can be used further for clinical purposes.

CS-based techniques exploit the inherent sparse nature of the ECG signals either in the time domain [5,6], or in the wavelet domain [4,7–10]. The conventional wavelet-based ECG compression methods [11] have higher data compression capabilities than CS, but when it comes to the real-time processing with minimum energy and computational cost, CS-based techniques outperform the wavelet-based methods [4]. Previous works in this area include the pioneering work by Mamaghanian et al. [4] who established and quantified the potential of CS for the first time for low complexity and energy-efficient data reduction in WBAN-enabled ECG monitors. Various design considerations were later studied by Dixon et al. [5] for CS-based data acquisition and reconstruction systems. In a similar framework, Zhang et al. proposed a system for fetal-ECG [6] and electroencephalograph (EEG) [12] remote monitoring using a block sparse Bayesian learning approach. Recent advances in the CS field are to incorporate signal structure information in the traditional CS reconstruction algorithms [7–9] with a goal to achieve superior reconstruction results. In the aforementioned works, the telemonitoring systems studied are limited to single channel ECG signals. However, cardiologists mostly prefer multi-channel or multi-lead ECG (MECG) signals for detailed diagnosis. This is because of the appearance of pathological features in more than one leads [13]. In literature, so far limited research [10,14] is available for MECG signals. This motivated the study of MECG signals in a CS framework for remote healthcare applications in the present work. The ECG signals acquired through different channels are not independent and they share mutual cardiac information common to all channels (Fig. 2). The source of this common information is the electrical heart vector whose projections in different directions lead to ECG signals in different channels. In such a scenario, conventional channel-by-channel processing of MECG is not optimal in terms of computational cost as well as system performance. Hence, new unified approaches are required for the correlated MECG signals.

Existing CS-based works [4,5,10] exploit only the sparsity of the ECG signals and thus ignore the important structural signal information that is known *a priori*. Recently, few works have been reported which use the prior signal knowledge to improve the decoding quality of CS [8,9]. Though, the above techniques exploit the anticipated signal information about the single channel ECG but they fail to utilize the spatial information shared across the channels. This is because of their design to process each ECG channel individually. In this work, we exploit the inter-channel correlation of MECG signals by processing all channels simultaneously

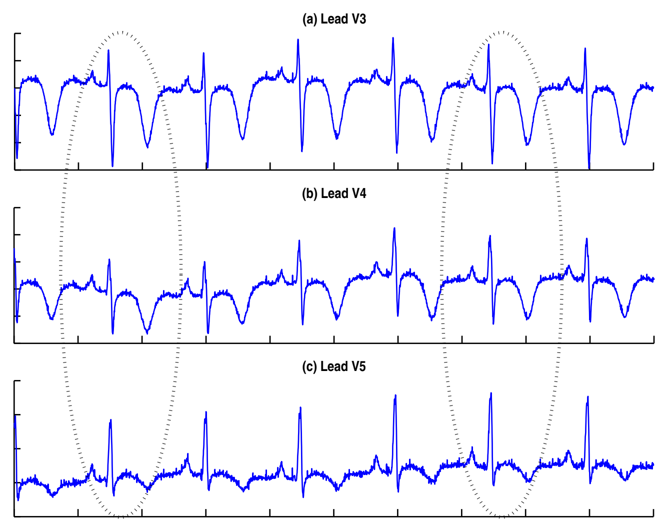

Fig. 2. ECG signals from three different channels showing the spatially correlated information (encircled beats) across the channels.

in a joint CS framework. A multiple measurement vector (MMV) CS model [15] is used for this purpose instead of traditional single measurement vector (SMV) CS model. The MMV, or row-sparse modeling of the MECG signals, helps in exploiting the natural group sparsity of different channels, which is present because of their inherent correlated structure. The MMV model relies on the fact that all the channels have a common support set, i.e., the ensemble is jointly sparse or row sparse. Approximately joint sparse behavior in wavelet domain (Fig. 3) enables the row sparse modeling of MECG signals.

A recently reported MMV-based work [14] has used a ℓ_1/ℓ_2-based mixed-norm minimization (MNM) algorithm for CS-based MECG data compression/reconstruction. MNM-based algorithms are known to be efficient for joint sparse recovery [16], however, they suffer from the disadvantage of amplitude dependence similar to traditional ℓ_1-norm minimization [17,18]. The nonzero rows corresponding to the higher coefficients in joint sparse representation are penalized more heavily than the rows corresponding to the lower coefficients during the optimization procedure [17]. Because of this, the reconstruction accuracy decreases, especially when the number of measurements is low (at higher compression ratios). This might be the reason that MNM algorithm used in [14] is not able to preserve clinically important larger wavelet coefficients