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Technical Note Multilead ECG data compression using SVD in multiresolution domain



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ABSTRACT

In this paper, multilead electrocardiogram (MECG) data compression using singular value decomposition in multiresolution domain is proposed. It ensures a high compression ratio by exploiting both intra-beat and inter-lead correlations. A new thresholding technique based on multiscale root fractional energy contribution is proposed. It selects the singular values depending on the clinical importance of the wavelet subbands. The proposed method is evaluated with the PTB Diagnostic ECG database. This compression method is embedded with a pulse amplitude modulated direct sequence-ultra wideband technology for transmission of the MECG data. This may be useful in telemonitoring services for the wireless body sensor network. A comparative study of computational time complexity has also been carried out. The results show that the proposed method can be executed at least three times faster than the existing methods. The storage efficiency is enhanced by 19 times using this method.

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1. Introduction

Wireless body sensor network (WBSN) is an emerging technology in telemedicine [1]. Recently, compressive sensing (CS) based compression methods [2-5] for single lead electrocardiogram (ECG) and fetal ECG signals have been evaluated in WBSN system. These methods are suitable for on-body sensors due to their nonadaptive nature and fast sampling. For diagnostic decisions, however, cardiologists use multilead ECG (MECG) more often compared to single lead ECG [6]. The standard MECG data consist of 12-lead ECG signals. This requires about 5.76 MB $(12 \times 16 \times 500 \times 60 \text{ bits})$ storage volume for 1 min duration MECG data sampled at 500 Hz with 16 bits/sample. This demands large memory space in WBSN systems. Also due to increase in number of leads, the energy consumption increases and transmission becomes inefficient for real-time applications. Hence, these CS based systems may not be suitable for multiphysiological signals because of their poor performance in compression ratio (CR, a maximum CR of 60–75% i.e. 2.5–4:1), and consequently, a low compression rate [7]. An efficient compression method for MECG data can resolve these issues. At the same time, it is also important to preserve the clinical information in the processed data.

The existing ECG compression methods exploit intra-beat [8–10] and inter-beat correlations [11,12] present in the ECG

http://dx.doi.org/10.1016/j.bspc.2015.06.012 1746-8094/© 2015 Elsevier Ltd. All rights reserved. signal. Recently, wavelet transform (WT) based compression methods have become popular [13–18]. The multiresolution property of the WT grossly segments the morphological features (P-wave, QRS-complex and T-wave) of the ECG signal into different subbands [15,16,19]. This has been exploited for preserving the clinical information in the compressed ECG data. Sharma et al. [17] have proposed a multiscale principal component analysis (MSPCA) based compression method. It uses only inter-lead correlation of the MECG data. This data can be presented in two ways. Either the rows and columns correspond to the ECG leads and their samples respectively or vice-versa. The correlation matrix (*AA*^T, where *A* is the data matrix) used in the PCA based method can capture either inter-lead or intra-beat correlation, depending on the arrangement of the MECG data.

Wei et al. [12] have proposed a singular value decomposition (SVD) based compression method for single lead ECG data. A hybrid ECG compression method based on SVD and discrete WT (DWT) is proposed in [20]. For implementation of SVD, the single lead ECG samples are presented as 2-D array data. The signal segments corresponding to successive ECG cycles (or periods) are arranged in rows or columns of the 2-D array. As ECG signal is quasi-periodic in nature, it requires period normalization for such an arrangement. However, the MECG is a 2-D array data and the timing information across all the leads is same. Therefore, SVD can be directly implemented on this data without any period normalization. Such an implementation can help exploit both intra-beat and interlead correlation. Moreover, the clinical information concerning the ECG morphological features can be processed effectively, if multi-

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scale analysis is added to this scheme. These features include the duration, amplitude and shape of the PQRST waves that are used primarily for clinical diagnosis [19,12,21,15]. This motivates us to propose a multiscale SVD (MSVD) compression method for MECG data. This work does not deal explicitly with the interbeat redundancy as it requires additional computations for QRS detection.

The highlights of the proposed method are summarized as follows:

- a multiscale SVD based compression algorithm for multilead ECG data has been proposed,
- it exploits intrabeat and interlead correlations of wavelet coefficients,
- a new thresholding technique is proposed,
- the algorithm outperforms the existing literatures for MECG data in terms of CR and computational time,
- simulation studies have been performed for WBSN applications by comparing with the state-of-art algorithms.

Rest of the paper is organized as follows. Section 2 presents the proposed multiscale SVD (MSVD) method for MECG data and a new thresholding technique for singular values. Section 3 describes the compression performance and comparison with existing methods. Simulations study on transmission of MECG data by encoding generated bit streams for WBSN applications is presented in Section 4. Also the computational complexity of the proposed method is carried out. Finally, conclusions are drawn in Section 5.

2. Method

In this section, an MSVD based data compression method for MECG data is proposed. In the standard 12-lead ECG system, four leads (III, aVR, aVL, aVF) linearly depend on the leads I and II [10]. Therefore only eight independent leads are processed. For most of the analysis in this work, MECG data refers to 8-lead ECG signals. Fig. 1 shows the block diagram of the proposed MECG data compression and reconstruction. The compression of MECG data consists of preprocessing, DWT, MSVD and coding. Prior to MSVD compression, the MECG data is rearranged for maximum correlation, first the six precordial leads (V_1, \ldots, V_6), then I and II [10]. During preprocessing, the raw MECG data is prepared for further processing. It consists of removal of baseline-wandering and amplitude normalization [17,22]. Normalization guarantees



Fig. 1. Block diagram of MECG data (a) compression and (b) reconstruction using multiscale SVD.

that all significant coefficients be less than one. This helps in further processing of the normalized coefficients effectively. The normalized amplitude factor is transmitted to the receiver site which is helpful during reconstruction. Encoding of bit streams is carried out for transmission in a WBSN system in Section 4. The reconstruction consists of decoding, MSVD restoration, IDWT and postprocessing.

2.1. Proposed multiscale SVD for MECG data

The proposed MSVD technique has three major steps: multiresolution analysis of MECG data, SVD on subband matrices and thresholding of the singular values (SVs) to reduce dimensionality of orthogonal and singular value matrices.

2.1.1. Multiresolution analysis of multilead ECG data

The multiresolution analysis (MRA) property of DWT is applied to each lead of the preprocessed MECG data ($\mathbf{X}_{m \times n}$) individually, where *n* and *m* represent the number of leads and ECG samples of each lead, respectively. Then the wavelet transformed coefficients corresponding to a particular subband of each lead are arranged to form a subband matrix. This result in L+1 subband matrices, where $L = \lfloor \log_2 F_s - 2.96 \rfloor$ is the number of decomposition levels and F_s is the sampling frequency. Based on different sampling frequencies, the value of *L* that satisfies the frequency span of the significant PQRST features of the ECG signal is heuristically derived [21]. A brief description on multiscale decomposition of MECG data is presented in [17]. L+1 subband matrices consist of one approximation subband matrix (\mathbf{A}_{L}) and L number of detail subband matrices $(\mathbf{D}_{L}, \mathbf{D}_{L-1})$ \dots, \mathbf{D}_1). These multiscale matrices contain grossly segmented information of the original signals. The dimensions of these subband matrices, **A**_L and **D**_i, *j* = *L*, ..., 1, are given as $m/2^{L} \times n$ and $m/2^{j} \times n$ respectively. The decomposition coefficient (DEC) matrix is formed by uniting $\mathbf{A}_{\mathbf{L}}$ and $\mathbf{D}_{\mathbf{L}}$, $\mathbf{D}_{\mathbf{L}-1}$, ..., \mathbf{D}_{1} , and can be represented as

$$\mathbf{DEC}_{m \times n} = \left[\mathbf{A}_{\mathbf{L}}^{\mathbf{T}} \mathbf{D}_{\mathbf{L}}^{\mathbf{T}} \mathbf{D}_{\mathbf{L}-1}^{\mathbf{T}} \dots \mathbf{D}_{1}^{\mathbf{T}}\right]^{T}$$
(1)

2.1.2. SVD of subband matrices

After constructing the subband matrices, each one is decomposed using SVD as follows:

$$\begin{aligned} \mathbf{A}_{\mathbf{L}} &= \mathbf{U}_{\mathbf{A}_{\mathbf{L}}} \mathbf{S}_{\mathbf{A}_{\mathbf{L}}} \mathbf{V}_{\mathbf{A}_{\mathbf{L}}}^{l} \\ \mathbf{D}_{\mathbf{j}} &= \mathbf{U}_{\mathbf{D}_{\mathbf{j}}} \mathbf{S}_{\mathbf{D}_{\mathbf{j}}} \mathbf{V}_{\mathbf{D}_{\mathbf{i}}}^{T} \end{aligned} \tag{2}$$

where \mathbf{U}_{A_L} , \mathbf{V}_{A_L} , \mathbf{U}_{D_j} , \mathbf{V}_{D_j} , j = 1, ..., L are unitary matrices and \mathbf{S}_{A_L} , \mathbf{S}_{D_j} are singular value matrices. The columns of \mathbf{U}_{A_L} , \mathbf{U}_{D_j} and \mathbf{V}_{A_L} , \mathbf{V}_{D_j} are left and right singular vectors of \mathbf{A}_L and \mathbf{D}_j , respectively. The left and right singular vectors are the basis functions that represent the sample-wise and lead-wise data variability in wavelet domain, respectively. After applying the SVD on the multiscale matrices, it is expected that the grossly segmented morphological features do appear in the eigen space.

Let **U** contain the unitary matrices of all approximation and detail subband matrices i.e. $\mathbf{U} = [\mathbf{U}_{A_L}; \mathbf{U}_{D_L}, \dots, \mathbf{U}_{D_1}], \mathbf{U} \in \mathbb{R}^{m \times m}$. Similarly, **S** and **V** can be represented as $\mathbf{S} = [\mathbf{S}_{A_L}; \mathbf{S}_{D_L}, \dots, \mathbf{S}_{D_1}], \mathbf{S} \in \mathbb{R}^{m \times n}$ and $\mathbf{V} = [\mathbf{V}_{A_L}; \mathbf{V}_{D_L}, \dots, \mathbf{V}_{D_1}], \mathbf{V} \in \mathbb{R}^{n \times n}$, respectively. Each singular matrix of **S** has *n* nonzero values. For example, the approximation subband singular value matrix can be represented as $\mathbf{S}_{A_L} = [diag\{\sigma_{A_{L_1}}, \sigma_{A_{L_2}}, \dots, \sigma_{A_{L_n}}\}: 0] = [\mathbf{\hat{S}}_{A_L}: 0], \sigma_{A_{L_1}} \ge \sigma_{A_{L_2}} \ge \cdots \ge \sigma_{A_{L_n}} > 0$. Consequently, the m - n columns of the unitary matrix will have no effect in the product of unitary matrix with the singular value matrix (2). Hence, **U** can be replaced with $\mathbf{\hat{U}}$ by removing m - n columns. The reduced SVD can be expressed as

$$\begin{aligned} \mathbf{A}_{\mathbf{L}} &= \hat{\mathbf{U}}_{\mathbf{A}_{\mathbf{L}}} \hat{\mathbf{S}}_{\mathbf{A}_{\mathbf{L}}} \mathbf{V}_{\mathbf{A}_{\mathbf{L}}}^{T} \\ \mathbf{D}_{\mathbf{j}} &= \hat{\mathbf{U}}_{\mathbf{D}_{\mathbf{i}}} \hat{\mathbf{S}}_{\mathbf{D}_{\mathbf{i}}} \mathbf{V}_{\mathbf{D}_{\mathbf{i}}}^{T} \end{aligned} \tag{3}$$

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