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Electrocardiogram beat type dictionary based compressed sensing for telecardiology application

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ABSTRACT

Effective compression of Electrocardiogram (ECG) is a vital task in telecardiology application. Compressed sensing (CS) offers a low energy implementation based solution to the telecardiology system. In this work, an efficient beat type dictionary based ECG-CS approach is proposed. The main objective of this study is to incorporate the advantages of both beat type dictionary and non-uniform random sensing matrix for effective patient-agnostic based signal recovery. Unlike patient-specific dictionary based CS approaches, the proposed beat type dictionary offers high-quality signal recovery without the training stage for individual ECG record. The performance of the proposed scheme is evaluated using the standard MIT-BIH database. The quantitative performance matrices such as compression ratio (*CR*), percentage root mean square difference (*PRD*1), root mean square error (*RMSE*), signal to noise ratio (*SNR*) are compared with the existing CS approaches to quantify the efficacy of the proposed scheme. At *PRD*1 of 9%, the proposed beat type dictionary-based method presents 33.5% more *CR* than adaptive dictionary-based CS approach. An in-depth analysis of the results highlights that the proposed beat type dictionary based CS scheme offers an efficient solution to the patient-agnostic based signal recovery and can be served as a potential component in the computer-based automated medical system.

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1. Introduction

The rapid growth of population is the biggest challenge to the modern healthcare service in today's era. Poor doctor to patient ratio is a leading situation of almost all underdeveloped and developing countries. Computer-based automated telemedicine system can be a better solution for it [1,2]. In the telemedicine system, physiological signals like Electrocardiogram (ECG), Electroencephalogram (EEG), etc. are acquired from the patient body through various sensors. Next, these signals are processed using advanced automated computing system for local treatment and transmitted to a remote health-care unit for better diagnosis on demand [3–9]. For proper diagnosis, efficient signal processing tools are always essential. Over the last few years, several advanced methods have been proposed in the literature for automated processing of physiological signals [10–16]. Hence, biomedical signal processing is an active research topic in today's technology. Cardiovascular disease is one of the leading causes of death of people globally. Electrocardiogram (ECG) is the primary tool used for the diagnosis of various cardiac disorders [17–27]. Computer-based automated telecardiology is a popular trend in modern healthcare technology. However, the performance of such system is restricted due to the power-hungry nature of wireless transmission devices which limits the battery life of the wireless sensor nodes [28]. Wavelet-based lossy compression techniques [29,30] are popular for ECG signal compression, but the requirement of overall power associated with these techniques is quite high. Compressed sensing (CS) is a new emerging signal processing technique that offers to capture signal information with a sampling rate lower than the traditional Nyquist sampling. Unlike traditional Nyquist based compressed techniques, in CS, compression and sensing occur simultaneously, that makes it energy efficient in signal acquisition [28]. The previous literature [31,32] acknowledge the superiority of the CS approach over discrete wavelet transform (DWT) based compression technique in terms of signal acquisition complexity and computational complexity.

Several researchers have contributed numerous research articles on CS based ECG compression technique. Mamaghanian et al. [31] have presented a comparative study between CS and DWT based ECG compression. The standard wavelet dictionary is used for CS scheme. Their study suggests that the CS-based method offers 37.1% more battery life than the traditional DWT based sensor nodes. However, the CS-based scheme shows poor signal quality in terms of percentage root mean square difference (*PRD*) than the DWT based compression techniques. Mishra et al. [33] sug-

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gested that rbio3.7 and rbio3.9 wavelet dictionaries present an optimum sparse representation of ECG signals. In [34], the ECG signal is thresholded in the time domain to obtain the sparse representation which results in loss of the low amplitude information: P and T waves. Liu et al. [35] proposed a block sparse Bayesian learning (BSBL) based CS methodology for telemonitoring of fetal ECG. Though wavelet dictionary presents a sparse representation of natural signals, the quality of CS recovery signal through wavelet dictionary is quite poor. A new approach called dictionary learning is introduced, where the sparsifying dictionary is generated through an iterative learning process from the test signal itself. Polania et al. [36] proposed a dictionary learning based CS method which utilized prior knowledge of signal structure at various wavelet sub-band levels. In [28,37] patient-specific dictionary based CS approaches have been proposed. For training of patient-specific dictionary, a large portion of test ECG data is required which increases the transmission cost. For patient-agnostic based recovery, these approaches show poor performance. Craven et al. [32] proposed an adaptive dictionary (AD) learning based CS methodology. It utilizes two different dictionaries for the recovery of ECG signal components: without QRS complex and with QRS complex. According to the signal characteristic proper dictionary is employed for sparse recovery and signal reconstruction. The scheme shows better performance than the previous methods. However, it uses patient-specific dictionary learning which requires a large portion of test ECG that increases wireless transmission cost.

Based on the above discussion, it can be acknowledged that compressed sensing can be used efficiently for telemedicine application. However, due to the lack of proper sparsifying dictionary, maintaining a proper quality of the recovered signal from a few measurements is a challenging task till date. Dictionary learning approach for sparse recovery of the signal shows a better response than the wavelet dictionary but the training of dictionary requires a huge amount of signal transmission energy. Considering the aforementioned constraints, in this work an ECG beat type dictionary learning based CS approach is proposed. Due to the different abnormalities, the morphologies of the ECG beats are changed which enforces to use a specific dictionary for proper reconstruction. Unlike the previous state-of-the-art schemes, in this study, three types ECG beat: normal, premature ventricular contraction (PVC) and paced dictionaries are generated, and according to the morphology of the ECG beats, the corresponding beat type dictionary is applied for recovery of the different ECG signals. With this patient-agnostic approach, the training phase for individual signal reconstruction can be eliminated which will make the scheme energy efficient. Standard MIT-BIH arrhythmia database (MITDB) [38], normal sinus rhythm database (NSRDB) [39] and compression test databased (CDB) [40] ECG signals are used to evaluate the performance of the proposed scheme. The efficacy of the described method is measured by analyzing compression ratio (*CR*), percentage root mean square difference (*PRD*, *PRD*1), root mean square error (*RMSE*), signal to noise ratio (*SNR*) and fractional distortion measure (*FDM*).

The rest of the paper is organized in the following manner. Section 2 describes the compressed sensing (CS) and the dictionary learning (DL). The detail description of the proposed scheme is presented in Section 3. Section 4, illustrates the results and discussions, which will be followed by the conclusion of this study in Section 5.

2. Background knowledge

2.1. Compressed sensing (CS)

Compressed sensing (CS) is an advanced signal processing approach that allows to capture the signal information with less amount of measurement than traditional Nyquist based signal acquisition [41,42]. Consider, X denotes the original signal, such that $X \in \mathbb{R}^N$. X has sparse representation in the dictionary ψ such as

$$X_{N\times 1} = \psi_{N\times P}\alpha_{P\times 1} \tag{1}$$

Here α is the sparse representation of X in dictionary ψ. Consider, Y defines the measurement vector such that $Y \in \mathbb{R}^M$ and $M \ll N$, then according to the CS theory

$$\begin{aligned} Y_{M\times 1} &= \phi_{M\times N}X_{N\times 1} \\ Y_{M\times 1} &= \phi_{M\times N}\psi_{N\times P}\alpha_{P\times 1} \end{aligned} \tag{2}$$

Here ϕ denotes the sensing matrix. The preferable choice of sensing matrix is random value entry matrix [41].

For recovery of the original signal from the compressed measurement data, the sparse nature of X in the dictionary ψ is utilized. An $l1$ norm minimization algorithm is applied for solving this problem. As $M \ll N$, an infinite number of solutions can be found and from those the optimum solution that provides the best approximation of X in the dictionary ψ is extracted. The sparse recovery problem can be modelled as follows [43].

$$\min \|\alpha\|_1 \quad \text{subject to} \quad Y = \phi\psi\alpha \tag{3}$$

In this work, basis pursuit (BP) method is used for $l1$ norm minimization. BP has the advantage of being independent of sparsity level than other greedy algorithms [34].

2.2. Dictionary learning (DL)

Standard wavelet dictionary offers the sparse representation of the natural signals, but at few number of measurements, the standard wavelet dictionary fails to recover the original signal properly [43]. Dictionary learning (DL) is an iterative learning process where the dictionary is generated from a set of training signals [44]. Consider, X^t is the set of training signals of dimension $N \times J$, from this training set the optimum dictionary D of dimension $N \times P$ (where $P \ll J$) is extracted through DL process. The DL problem can be modelled as follows [37].

$$\min_{D,A} \left\{ \left\| X^t_{N\times J} - D_{N\times P}A_{P\times J} \right\|_F \right\} \quad \text{subject to} \quad \left\| A_j \right\|_0 < L \tag{4}$$

Here A is the sparse representation of the training matrix, A_j denotes the sparse representation of j^{th} signal of the training set, $\| \|_F$ defines the Frobenius norm and L is sparsity level (number of non-zero values in the data). Each element in the dictionary is known as atom. Two methods popularly followed for DL process are Method of Optimal Direction (MOD) [45] and K-means clustering singular value decomposition (K-SVD) [46].

3. Proposed beat type dictionary based CS scheme

The block diagram of the proposed beat type dictionary based CS scheme is demonstrated in Fig. 1. A detailed description of each stage is presented in the following subsections.

3.1. ECG signal compression

ECG signal is processed in frame-wise and length of each frame is empirically taken 192 samples [32]. The length of each frame is chosen such that the ECG segments can be categorized in QRS complex segment and non-QRS complex segment. A frame length with much longer can contain more than one QRS complexes which causes difficulty while choosing the particular dictionary. Again, by incrementing the number of span in the frame and corresponding sub-dictionaries, the resolution of the location of QRS complex

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