

Recent Trends in ECG Data Compression Approaches

***Butta Singh, Himali Sarangal and Manjit Singh**

Guru Nanak Dev University, Regional Campus, Jalandhar

Corresponding Author Email ID: bsl.khana@gmail.com

Abstract

ECG monitoring facilitates in providing accelerated health status of the concerned patient to the healthcare centre in case of the hostile cardiac behavior. For continuous monitoring of patient's health, the ECG signal is recorded for long time durations typically for several hours or few days. The storage of such massive volume of data requires large memory space. To combat with such a huge growth rate of memory requirement and data sparsity, many ECG compression and de-compression algorithm had already developed to represent the raw ECG in the processed format. In this paper, the review of approaches dealing with ECG data compression is presented. It also highlights the research challenges relevant to each domain.

Keywords:Electrocardiogram; ECG; Data Compression

Introduction

E-healthcare monitoring system enables an instantaneous analysis of patient physiological data. One of the best representatives of physiological signal is Electrocardiogram (ECG), which provides state of autonomic nervous system responsible for regulating cardiac activity [1]. In the modern era, cardiovascular diseases had emerged as one of the essential causes of mortality in both urban and rural areas [2], [3]. ECG monitoring facilitates in providing accelerated health status of the concerned patient to the healthcare centre in case of the hostile cardiac behaviour [4]. Cardiac monitoring using ECG signal is the best representative of heart's electrical functionality and had proven to be useful in the diagnosis of most of the heart diseases. Transmission of this compressed ECG via a communication channel introduces various security and privacy issues [5]. To counteract with these concerns, there is a need for implementation of efficient security protocols. To this effect, several algorithms have been developed in the past two to three decades [6].

For continuous monitoring of patient's health, the ECG signal is recorded for long time durations typically for several hours or few days. The storage of such massive volume of data requires large memory space, for example, a threechannel ECG signal sampled at a frequency of 1 kHz with 11 bits of resolution in three lead system of a particular patient, recorded for 24 h requires 928 MB of memory size per channel without any overhead. Such vast volume of data is expected to have intra and inter-beat correlation or inherent sparsity. ECG pos-

sesses the capability of reduction of redundant information through intra and interbeat correlation, which is the core cause of its data compression[7]. To combat with such a huge growth rate of memory requirement and data sparsity, many ECG compression and de-compression algorithm had already developed to represent the raw ECG in the processed format [8].

In general, compression methods can be classified as lossy and lossless [9]. A better value of Compression Ratio (CR) is achieved when lossy methods are used but at the cost of the reconstruction error. An efficient integrity of the reconstructed data is ensured using lossless ECG data compression methods, but with the compromised CR, typical 2-4 CR with 0% reconstruction error has been reported in the literature [10]. The performance of ECG data compressor is usually being measured by the CR at the desired reconstruction error. Generally, the reconstruction error is being calculated by the Percentage Root mean square Difference (PRD) at the receiver end, after the process of decompression. Many researchers have proposed ECG compression techniques by treating One Dimensional (1D) ECG signal as a Two Dimensional (2D) image and exploiting the inter and intra-beat correlations by encoder [11]–[13]. These techniques broadly consist of the steps: QRS detection, ECG segmentation, pre-processing, and transformation. The “cut and align beats approach and 2D Discrete Cosine Transform (DCT)” and “period normalization and truncated Singular Value Decomposition (SVD) algorithm” are available pre-processing techniques to get good compression results in ECG

[14], [15]. This pre-processing is also often associated with the use of state-of-the-art image encoders, like JPEG2000, H.264/AVC, etc.

2. RESEARCH CHALLENGES

In this section, the literature survey dealing with ECG data compression is presented. It also highlights the research challenges relevant to each domain.

2.1. ONE-DIMENSIONAL ECG DATA COMPRESSION TECHNIQUES

In ECG data compression techniques, the direct and the transformed domain are used to exploit the redundancy in the signal. Thresholding the transformed domain coefficients significantly reduces the data size without losing the significant information [23]. Many 1D and 2D domain based compression methods are reported in the literature. The direct data compression method analyzes and reduces data points in the time domain. Jalaeddine et al. [23] had surveyed various direct data ECG compression schemes which include Turning Point (TP), Amplitude Zone Time Epoch Coding (AZTEC), improved modified AZTEC technique, Co-ordinate Reduction Time Encoding System (CORTES), the delta algorithm and the Fan algorithm. Cox et al. [24] proposed AZTECH algorithm rhythm analysis the advantage of this method lies in its ability of high data reduction ratio but suffers from loss of data fidelity due to the presence of discontinuity that occurs in the reconstructed ECG waveform. Kumar et al. [25] developed improved modified AZTECH technique in which the statistical parameters of the signal to be compressed are computed, and they adjust themselves to the nature of the signal by recalculating the threshold value. The authors have concluded that using least square polynomial smoothing filter a significant reduction in PRD was obtained for a typical value of $CR=2.76$, the threshold value of 0.010, PRD value with and without smoothing filter were 4.54 and 6.56 respectively. Kumar et al. [26] had surveyed AZTEC, modified AZTEC, Fan, and scan along polygonal approximation techniques. The authors had also suggested some modifications in them, thereby making suitable for telemedicine purposes. In the modified version the CR value is high, and PRD value had gone considerably low for the same value of the threshold.

Recently, Mukhopadhyay et al. [27]–[29] proposed AS-CII based encoding methods to be employed for compression due to its simplicity, which enables them to be used in portable and mobile data ECG data monitoring

systems. The transformed method analyzes energy distribution by converting the time domain to some other domain.

Sur and Dandapat et al. [8] presented a prospective review of various ECG data compression methods like Fourier transform, Fourier descriptor, Karhunen–Loeve Transform (KLT), the Walsh transform, the DCT and the wavelet transform. To efficiently explore inter and intra beat correlations at the encoder, processing techniques for 2D ECG image were also discussed by the authors. In twodimensional ECG compression methods, the transformation is applied to the 2D representation of 1D ECG signals to improve the compression efficiency. Reddy et al. [30] devised Fourier descriptor based ECG data compression. The advantage of the proposed method was its capability to handle noisy records without any requirement of the postprocessing, which was duly justified by the value of on an average $CR=7$ and $PRD=7$, making it suitable for the morphological study. Batista et al. [31] developed an effective compression technique which was based on optimized quantization of DCT coefficients. The efficiency of the technique was verified on all 48 records of MIT-BIH arrhythmia database. The results of CR and PRD using the proposed technique for the 100th record were 10.2 and 3 respectively.

1.2. TWO-DIMENSIONAL ECG DATA COMPRESSION TECHNIQUES

Numerous researchers have reported ECG data compression procedures by formulating 2D arrays from ECG signals to better exploit the inter- and intra-beat correlations by the employed encoder [11], [12], [34]. 2D ECG compression method needs reliable and precise R-peak detection and segmentation for efficiently exploiting the intra-beat and inter-beat correlations. Since the length of each beat is different, an appropriate algorithm is needed to align the beats for maximizing the beat to beat correlation. The cut and align beats approach with 2D DCT [35] along with period normalization [36] are the existing pre-processing techniques that achieve decent ECG compression results.

Kumar et al. [37] reported a 2D ECG data compression algorithm based on singular value decomposition and wavelet difference reduction techniques. Eddie B. et al. [11] proposed a new lossy compression technique which focused on pre-processing by clamping minimum DC level of the period. After clamping, the process of complexity sorting was done through which an increase in the vertical smoothness of the image was achieved.

Different combinations of pre-processing methods were explored using JPEG2000 & H.264/AVC encoder.

In the analysis by Filho et al. [11], it was verified that this assumption does not hold for the large set of ECG signals of pathology subjects. One more pre-processing method consists of a QRS detector, period length normalization, Dc equalization, complexity sorting and image transformation as designed in [11].

3. DATABASE

The details pertaining to the selected ECG datasets are as follows

Standard MIT-BIH Arrhythmia database: The dataset contains 48 records of thirty minutes' duration having two-channel ambulatory ECG recordings [62]. The 11-bit resolutions over 10 mV ranges with the sampling frequency of 360 Hz per sample channel were recorded.

NSR database NSR database : It includes 18 ECG datasets of subjects with no significant arrhythmias; they include 18 records aged 26 to 50 with sampling rate 128 Hz and gain of 200 with 0 base.

CUVT database CUVT database: It comprises 35 ECG records of who experienced ventricular flutter, ventricular tachycardia, and ventricular fibrillation. The ECG signals are sampled at 250 Hz and gain of 400 with 0 base.

CSE database: This library has 125 ECG data sets (MO1_001 to MO1_125). The signal from these sets is sampled at 500 Hz with a peak 5mV quantization and 10-bit resolution. Each data record contains 15-channels of ECG signals including conventional 12 leads and 3 Frank leads.

PTB database PTB database: This database has 549 12 lead ECG records collected from 290 subjects (aged 17 to 87, average 57.2 years) Each subject is characterized by one to five ECG records. Each record contains 15 concurrently measured signals: the conventional 12 leads (I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6) organized with the 3 Frank ECG leads (Vx, Vy, Vz). The sampling frequency was 1000 Hz for each signal with a gain of 2000 and 0 base

4. CONCLUSION

The present work contributes and reviews in the area of ECG data compression mechanisms that can aid the telecardiology technology. The proposed approach can also satisfy the growing need for the processing of ECG signals directly in compressed and encrypted domains to ensure the patient's privacy protection

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