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Hybrid encoding algorithm for real time compressed electrocardiogram acquisition

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ABSTRACT

Tele-healthcare systems have shown a great promise toward flexibility in wireless medical signal collection and increased mobility of the patient to achieve early diagnosis. We describe a simple, lossy compression algorithm for single lead Electrocardiograms (ECG) using a hybrid encoding strategy, which can be utilized for patient monitoring application. It detects the ECG beats in real time, divides it into equal size 'plain' or 'complex' blocks based on complexity measure and allocate bits using two different principles to optimize the entropy (bits per sample efficiency) in the encoded bit-stream. With MIT BIH arrhythmia data at 1 kHz sampling and 10-bit quantization, the algorithm achieved an average CR and PRDN of 10.99 and 3.27 respectively, with average bit per sample value of 1.49. The average distortion in clinical signatures using PTB diagnostic ECG data was found to be less than 3%, which is clinically acceptable.

1. Introduction

Electrocardiogram (ECG) represents time averaged representation of tiny electrical impulses generated on heart muscles and their propagation along conduction fibers on atria and ventricles. It can provide vital information on cardiac functions and heart's rhythmic activities. Clinical features of ECG are obtained from wave durations and amplitudes of the constituent P, QRS, and T (with occasional U) waves and the segments PQ, ST and TP. Fig. 1 shows a typical ECG beat and prime diagnostic measurements. These are visually inspected by cardiologists for detection of heart abnormalities [1]. Over last fifty years, the extensive research on computerized measurement and analysis of ECG has been contributed by advancements in sensing technology, embedded systems, information and communication technology (ICT), and soft computing techniques. This has enabled remote acquisition of medical signals through personal or public communication networks using handheld gadgets. Portability, miniaturization and power consumption optimization are some of the challenges in current medical signal acquisition applications. With the contribution of microelectronics and materials science toward sensing technology, power efficient and patient friendly medical sensors have been developed [2–5]. Today's medical sensors integrate digital intelligence to perform front end processing like filtering and data compression at the acquisition site [6–8]. Tele-monitoring is an emerging area of biomedical technology that has shown great promise toward personal healthcare in the current century. With the proliferation of miniature, power-efficient and fast computing embedded circuits in medical instruments, tele-healthcare systems facilitate remote monitoring of cardiac patients, while allowing them in their normal activity [9,10]. Compact, low-cost radio frequency (RF) transceivers are now commercially available to be easily interfaced with these smart sensor modules to develop portable wireless ECG acquisition systems [11,12]. An important application of health-monitoring applications is body sensor network (BSN), where the different medical sensors, attached to patient body, form a network to route medical information to a local or remote host. Body area network (BAN), an adaptation of body sensor networks (BSN) in healthcare, has been applied in ambulatory health monitoring and quality of life (QoL) applications for elderly patients, like, in context aware sensing [13]. In such applications, compressed acquisition of bio-signals assumes special significance to enhance spectral efficiency of the wireless link and longer battery life of the sensor nodes. Out of the three energy consuming tasks, namely, sensing, computing and communicating, the last one consumes most, around 65% of the total [14,15]. A new approach, namely, compressed sensing or sampling (CS) [16,17] has been introduced which enables a sparse signal, originally

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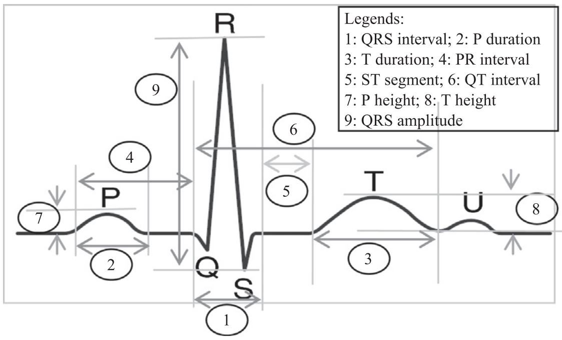

Fig. 1. A typical ECG lead plot and prime clinical features.

sampled at sub-Nyquist rate, be reconstructed with acceptable accuracy. The principle of CS has been used to reduce the power consumption in wireless sensor nodes [18] and for ECG acquisitions [19–21]. Another application is the capability to recognize 'pathological events' from the electrocardiogram in real time for clinical action [22,23] by caregivers.

Although a vast literature is available for ECG compression, many of them specially transform domain techniques are unsuitable for real time implementations due to their complexity as well as high buffer requirement. So, reducing the complexity and power consumption in real time ECG compressors still remains a challenge. For real-time telemonitoring application using packet by packet transmission, bits per sample (BPS) efficiency of the encoder plays an important role for effective link utilization. BPS (also called entropy measure) is number of bits engaged for encoding each sample of ECG data, and its low value indicates higher link throughput for real-time monitoring applications. Some recent works [24–27] on ECG compression using direct data compression (DDC) methods were analyzed by us. Although achieving a high compression in totality, their average BPS is high due to fixed length encoding. To the authors' knowledge, there has not been any attempt for implementing flexible bit-allocation for real time ECG compression using DDC methods. The proposed algorithm is therefore aimed to achieve a beat-by-beat compression with low entropy through a hybrid encoding, which employs block specific compression rules, one is using fixed-length and the other using variable length codes.

The prime contributions of the proposed algorithm are: (i) implementability in real-time monitoring using a low-end processor, (ii) optimum zonal sample selection to protect clinical information, and (iii) flexible bit-allocation (FBA) strategy or nibble combination (NC) based on zonal character of the ECG wave, while preserving the basic essence of delta encoding. At the same time, it is fully adaptive to the inter-beat variations in ECG morphology which are expected in real-time measurements. Preservation of clinical features (as shown in Fig. 1) in the encoded data stream is of paramount importance in diagnostic decision making. For compression algorithms, the reported works used percentage root mean squared difference (PRD), PRD normalized (PRDN), mean square error (MSE), root mean square error (RMSE) parameters [28] for reconstruction quality assessment. However, clinical acceptability of the reconstructed data is also important in telehealth applications [29,30]. The structure of the paper is as follows. Section 2 provides detailed description of the algorithm logic for the hybrid compression. Section 3 discusses the compression performance and reconstruction results, with three benchmark ECG databases under Physionet [31] along with the comparison with a few reported works. The conclusion section provides main outcome of the research.

2. Materials and methods

2.1. Beat detection and beat length adjustment

In this work, quantized ECG data at 10 bit resolution was used. For this, the Physionet data was quantized using Eq. (1)

$$y_q = round[(y_s \times g)/1000 + v_{dc}] \times Q \tag{1}$$

where y_q is the quantized value; y_s is the sample value in millivolt; g is the amplification factor (taken as 500); v_{dc} is the DC shift, taken as 2.5 and Q is the quantization factor (taken as 204 for 10-bit ADC). The R-peaks in the ECG dataset were detected by a sliding window of 40 ms using a slope detection based algorithm. The threshold was determined in the first 1500 samples. For each sample, 20 point upside and downside slope was computed using Eq. (2). The threshold (slp_th) was selected using highest average slope (slp_mx).

$$\begin{aligned} slp\_l(k) &= |y_q(k) - y_q(k-20)| \\ slp\_r(k) &= |y_q(k) - y_q(k+20)| \\ slp\_av(k) &= \frac{slp\_l(k) + slp\_r(k)}{2} \\ slp\_th &= 0.85 \times slp\_mx \end{aligned} \tag{2}$$

where slp_mx denotes maximum slp_av for first 1500 samples.

This threshold was used to detect the subsequent R-peaks in the dataset. Each R–R intervals were divided into 2:1 ratio (since T wave is normally wider than P wave) and the baseline point was detected in the TP segment in a search on 100 ms window around the boundary. The index with minimum absolute 15-point average slope around it (computed similar to Eq. (2)) was considered as the baseline point (blp). The entire array between blp_i and blp_{i+1} was taken as the current beat i. Each current beat was segmented using a block length of either 44, or 48 or 52 samples by 'beat length adjustment (BLA) logic' to counteract inter-beat variability in length. The BLA logic adjusts the length of each beat by re-allocating a few samples from start of following beat to the tail of preceding (current) beat, if required. This also ensures the last block-character is not hampered.

2.2. Complexity estimation and block character attribution

The proposed algorithm achieved beat by beat compression in real time by dividing an ECG beat into 'plain' and 'complex' blocks, PB and CB respectively, based on their information content or fluctuations. A typical ECG beat contains high fluctuations in 10–15% region as QRS complex (legend 1 in Fig. 1); low fluctuations in 30–40% region, realized by P and T waves, and equipotential wave segments in rest 45–60% region consisting of PQ, ST and TP (legend 3, 4 and 5 in Fig. 1). In real ECG measurements, these equipotential segments are obtained as low oscillations due to baseline wander. In the proposed approach, this zonal fluctuation was utilized by measuring the standard deviation (SD) in each blocks using Eq. (3)

$$SD_k = \sqrt{\frac{\sum_i (y_q(i) - \bar{y}_q)^2}{n}} \tag{3}$$

Usually the SD denotes the signal's energy. A fixed threshold was used to distinguish QRS regions from the others. The blocks with SD higher than the threshold value were designated as complex block (CB) and the rest as plain blocks (PB) using the following rule:

$$\begin{aligned} &\textit{if } SD_k \geqslant SD_{th} \\ &\quad block = \text{'}complex\text{'} \\ &\textit{else} \\ &\quad block = \text{'}plain\text{'} \end{aligned} \tag{4}$$