A 2D ECG Compression using Sample Entropy based Complexity Sorting Approach

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Abstract

In the present paper, an effectual sample entropy (SampEn) based, complexity sorting pre-processing technique has been proposed for 2D ECG matrix compression. The novelty of the introduced approach lies in its ability to compress the quasi-periodic ECG signal by exploiting the intra and inter-beat correlation. The proposed method comprises of following steps: 1) QRS detection, 2) Length normalization, 3) Dc equalization, 4) SampEn based nonlinear complexity sorting and 5) Compression using JPEG2000 Codec. The performance of the approach has been validated using various statistical measures over all the 48 records of standard MIT-BIH arrhythmia database. The novelty of the designed approach has been justified by its comparison with the contemporary state-of-art works existing in the literature. Average Quality score measure (QS) at different values of residual error percentage (PRD, PRD1024, and PRDN) are 41.24, 4.73, and 2.75 respectively. Also, the work reports extensive experimentations on different durations of all the ECG records (5-30 minutes with an incremental increase of 5 minutes). The proposed algorithm demonstrates significantly better performance in comparison to the other algorithms present in the literature, which was duly validated by performance measures.

Keywords: Electrocardiogram (ECG), Pre-processing, Data Compression, Sample Entropy, JPEG2000

1. Introduction

The incorporation of wireless communication technology in the field of the tele-cardiological platform has played a vital role in timely monitoring of Electrocardiogram (ECG) signal, especially for remote areas. The ECG signal that monitors the electrical activity of heart is usually characterized by its various set points (P, QRS, T) and intervals (PR interval, QT interval, and RR interval) that reflect the rhythmic electrical depolarisation and repolarisation of atria and ventricles [1].

ECG is having the possibility of reduction of redundant information through inter, and intra-beat correlation, which is the basic cause of its compression [2]. In general, ECG signal compression

techniques widely fall under three categories of the direct method, transformed method, and parameter extraction method. The direct data compression [3] method openly analyzes and reduces data points in the time domain, and the example includes turning point (TP), amplitude zone time epoch coding (AZTEC) [4], Improved modified AZTEC technique [5], coordinate reduction time encoding system (CORTES), the delta algorithm, the Fan algorithm [6], and the ASCII character encoding [7]–[9]. The transformed method analyzes energy distribution by converting the time domain to some other domain and example includes Fourier transform, Fourier descriptor [10], Karhunen–Loeve transform (KLT) [4], the fast Walsh transform [11], the discrete cosine transform (DCT) [12], DCT with modified stages [13], [14] and wavelet transform [15], and the compressed sensing [16], [17] and accuracy driven sparse model [18]. The parameter extraction method is based upon dominant feature extraction from the raw signal; examples include neural based or syntactic methods [19], peak picking and linear prediction method [20].

Many researchers have proposed ECG compression techniques by treating ECG signal as a two dimensional (2D) array and exploiting the inter- and intra-beat correlations by the encoder [21]–[23]. The "cut and align beats approach with 2D DCT" along with "period normalization and truncated SVD algorithm" are the available preprocessing techniques that achieve good ECG compression results [24], [25]. This kind of preprocessing is also often associated with the use of state-of-the-art image encoders, like JPEG2000. The preprocessing method, proposed here is a modification of technique presented by [21], [23]. In [22], the authors proposed a lossy compression method based on converting the ECG signal into 2D ECG array. A period sorting based preprocessing approach was introduced, which consists of a length-based ordering of all periods. The authors exploited inter and intra-beat dependencies to compress irregular ECG signals. The Inter beat correlation exists in the works by Chou *et al.* [22]. They formulated 2D ECG array by sorting them in ascending order according to period length. And Inter beat correlation among similar period lengths were perceived. In the analysis by Filho *et al.* [21] it is verified that this assumption does not hold for the large class of ECG signals where some pathology is present. Another preprocessing method consists of QRS detector, period length normalization, Dc equalization, complexity sorting and image transformation as proposed in [21]. The technique focused on the preprocessing stage by reducing the vertical high-frequency content of the 2D array.

Although the vertical, high-frequency content of the resulting 2D ECG array has been reduced by Dc equalization and variance based linear complexity sorting techniques, but still adjacent lines may be very dissimilar by following this preprocessing mechanism. However in some cases, it fails to guarantee the maximum similarity across adjacent periods. As ECG is a quasi-stationary signal, the variance based linear complexity sorting operation, that is used in [21] can be further improved by nonlinear processing typically using entropy based complexity sorting. Physiological system like cardiovascular system is composed of many nonlinearly interacted interdependent subsystems,

resulting highly complex signals. Many methods have been used to evaluate complexity, using both linear and nonlinear measures. Methods based on linear modeling are widely known and standardized. However, as a complex system, the cardiovascular system might be better assessed by nonlinear methods. Sample entropy (SampEn) is a nonlinear metric used to measure the irregularity of a time series [26], [27]. The main objective of the present paper is to explore the SampEn based nonlinear complexity indices for sorting and rearrangement of the rows of the 2D ECG matrix array from the simplest to the more complex ones.

The rest of this paper is organized as follows, Section 2 consists of database and performance measure description; justification to use the sample entropy based sorting is discussed in Section 3. Section 4 describes the proposed 2D ECG processing mechanism; Section 5 demonstrates the experimental results; finally, Section 6 concludes the paper.

2. ECG Database and Performance Measures

The Massachusetts Institute of Technology (MIT) supplies some valuable resources for various research projects like heart rate variability analysis and ECG compression. These resources include databases, containing recorded physiological signals and software for creating, viewing and analysing such recording. In the present study, ECG samples from Arrhythmia Database [28] (http://ecg.mit.edu) have been taken for investigation of the efficiency of the proposed method. The Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory. The 11-bit resolutions over 10 mV ranges with sampling frequency of 360 Hz per sample channel were recorded. Tests were made with second channel of all 48 records of this database.

To access the proposed pre-processing technique's efficiency, first 21,600 samples (10 min duration) were used and evaluated with following data compression metrics [12], [13], [18-20], [29]. Performance statistics were also computed for varying durations of the ECG records (5, 10, 15, 20, 25 and 30 minutes) thereby indicating the suitability of the designed approach for any length of ECG data.

The various performance metrics are defined as follows:

Compression Ratio (CR)

The CR provides information about the degree by which the compression algorithm removes the redundant data. Higher the *CR* less number of bits required to store or transmits the data which can be defined as

$$CR = \frac{B_0}{B_c} \tag{1}$$

Where, B_0 is the total number of bits required to represent original data and B_c total number of bits required to represent compressed data along with the side information needed for retrieval of original data. In our database setting

$$CR = \frac{11 \times f_s \times N}{B_{c2d} + B_s} \tag{2}$$

Where f_s is the sampling frequency, N is the total number of samples in one dimensional (1D) ECG signal, B_{c2d} is the total number of bits in compressed 2D ECG and B_s is the bits required to store the side information

Percentage Root Mean Square Difference (PRD)

It is a measure of acceptable fidelity and degree of distortion introduced during compression and de-compression algorithm

$$PRD(\%) = 100 \times \sqrt{\frac{\sum_{n=1}^{N} (X_s(n) - X_r(n))^2}{\sum_{n=1}^{N} (X_s(n))^2}} \tag{3}$$

Where, $X_s(n)$ and $X_r(n)$ is the original ECG data and reconstructed ECG data respectively.

Percentage Root Mean Square Difference, with Base removed (PRD1024)

$$PRD1024(\%) = 100 \times \sqrt{\frac{\sum_{n=1}^{N} (X_s(n) - X_r(n))^2}{\sum_{n=1}^{N} (X_s(n) - 1024)^2}} \tag{4}$$

Percentage Root Mean Square Difference, Normalized (PRDN)

It is normalized version of PRD, PRDN, which does not depend on the signal mean value $\overline{X}$

$$PRDN(\%) = 100 \times \sqrt{\frac{\sum_{n=1}^{N} (X_s(n) - X_r(n))^2}{\sum_{n=1}^{N} (X_s(n) - \overline{X})^2}} \tag{5}$$

Root Mean Square Error (RMS)

It provides measure of error in reconstructed signal with respect to original signal.

$$RMS(\%) = 100 \times \sqrt{\frac{\sum_{n=1}^{N} (X_s(n) - X_r(n))^2}{(N-1)}} \tag{6}$$

Signal to Noise Ratio (SNR)

SNR, measure of degree of noise energy introduced by compression in decibel (dB) scale. The SNR definitions are in accordance with that existing in literature as given by Lee *et al.* [13] and Zigel *et al.* [29].

$$SNR = 10 \times log\left(\frac{\sum_{n=1}^{N} (X_s(n) - \overline{X})^2}{\sum_{n=1}^{N} (X_s(n) - X_r(n))^2} \right) \tag{7}$$

Quality Score (QS)

It is the ratio between the CR and PRD. The QS is a very rational performance indicator when it is difficult to estimate the best compression method while taking into account the reconstruction errors as well. Higher the score better is the compression method. As prevalent in literature QS can be computed for different versions of PRD thereby facilitating fair comparison with other algorithms[13].

$$QS_{PRD} = \frac{CR}{PRD} \tag{8}$$

$$QS_{1024} = \frac{CR}{PRD1024} \tag{9}$$

$$QS_{PRDN} = \frac{CR}{PRDN} \tag{10}$$

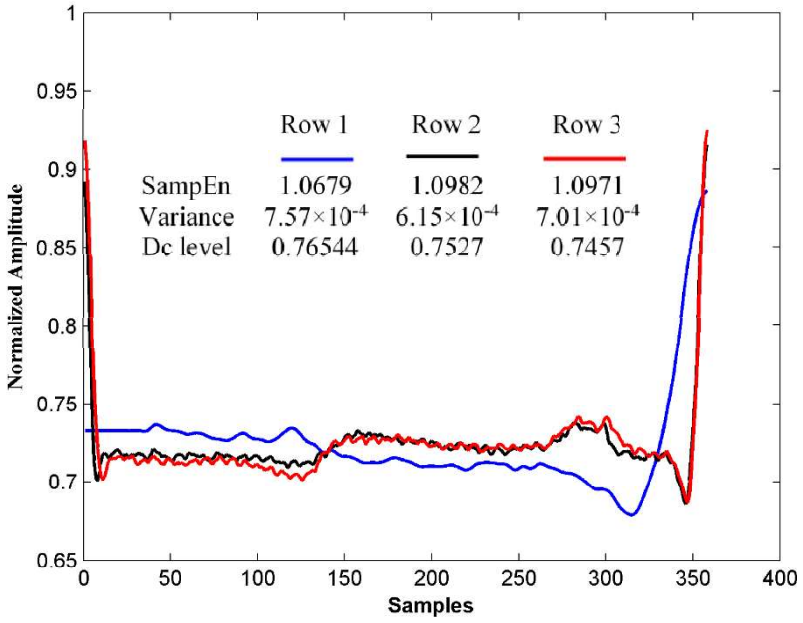
3. Why SampEn based Sorting

There is a fundamental difference between regularity parameters, entropy measures, SampEn, and variability estimators, such as variance. SampEn is a regularity, not a magnitude statistic [26]. The primary utility of SampEn is to uncover subtle complexity or alterations in long-term data that are not otherwise apparent. An entropy rate measurement for noisy and short data was introduced by Pincus, called approximate entropy (ApEn) family. ApEn is a biased estimate, taking into account self-occurrences of patterns [27]. Furthermore, it is inconsistent for different parameter values and time series length. SampEn eliminates the self-count bias, being more consistent than ApEn [26], [30], [31]. For the sake of illustration, both the variance and SampEn based sorting for first three row segments of record '100' from MIT-BIH arrhythmia database after Dc equalization is demonstrated in Fig. 1a. It provides the complexity analysis for Row 1, 2 and 3. The Dc equalization along with the normalized amplitude limits the maximum dynamic range of the ECG segments from 0-to-1. The scale for the normalized amplitude shown on y axis of Fig. 1a has been computed by dividing the

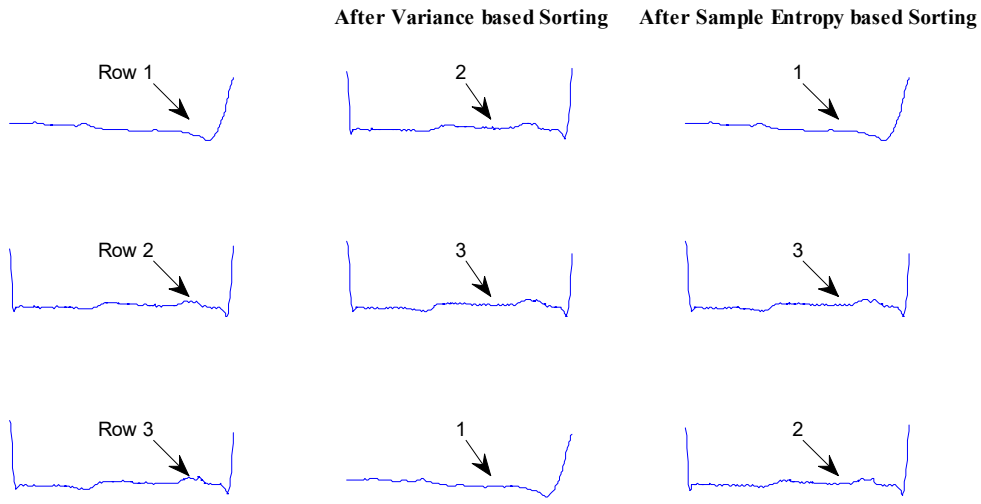
sample values by the maximum amplitude. The maximum value has been computed for the complete considered ECG time duration for a particular record.

The Dc levels used for the first three rows of record 100, are computed by taking the mean of the respective ECG beats. The obtained Dc values are provided in legend entries in Fig. 1a. Moreover, the minimum Dc level attained was 0.7143 with an offset of 0.01 that ensures each formulated ECG image has positive pixel values.

Variance and SampEn for these three rows are 7.57×10^{-4}, 6.15×10^{-4}, 7.01×10^{-4} and 1.0679, 1.0982 and 1.0791 respectively when computed over normalized values of ECG segment. Row 1 reveals the highest complexity in terms of variance, but in terms of SampEn row 2 has highest complexity. After variance based sorting the ascending order of segments will be row 2, row 3 and row 1. But for SampEn based sorting, an order will be row 1, row 3 and row 2 (Fig. 1b). SampEn based sorting can be validated by visual inspection of these three row segments. As depicted in Fig. 1a, tracing row 1 appears to be less complex as compared to other rows. As SampEn based complexity sorting reorders the ECG beats based upon ascending values of SampEn. Which leads to the exploration of the similarity among the ECG beats via increased randomness.



(a)



(b)

Fig. 1. First three consecutive row segment with SampEn, Variance, Dc value comparison of record 100 of MIT-BIH ECG arrhythmia database a) Row1, Row 2 and Row 3 b) Ordering after variance and SampEn based sorting

4. Proposed 2D ECG Preprocessing Technique

As shown in Fig. 2, there are four basic stages for compression and five for reconstruction process of proposed 2D ECG compression technique. The compression stage precedes the acquisition of ECG data from the standard MIT-BIH arrhythmia database that facilitates the comparative analysis and validation of proposed technique. Details of this database have been already discussed in section 2. The first and second stage involves QRS detection and R peak based ECG segmentation [32]. In ECG segmentation, ECG samples from one R peak to next R peak are retained in one segmented block, and each block (Row wise) is vertically stacked to form 2D ECG array. The third stage is the conjunction of interpolation and Dc equalization. Interpolation is needed for period normalization, and Dc equalization is required to reduce the vertical high-frequency contents of 2D ECG array. The fourth stage further eliminates the high frequency content between adjacent rows in the ECG array by exploiting the SampEn based complexity sorting. The adjacent rows are reordered in terms of increased inter beat randomness in a step-by-step manner. This stage leads to improved correlation among adjacent rows. Alternatively, this reduces the high frequency content, resulting in better compressor performance. The resulting array was encoded through a standard JPEG2000 [33] encoder, which provides precise rate control and progressive quality. The resulted compressed 2D ECG array along with side information can be transmitted over cloud or a base station from the remote place. It can be easily reconstructed at the receiving end. The first stage of the reconstruction process is to split the side information and compressed ECG matrix from the merged data that is coming from the communication channel followed by the second stage of SampEn based resorting

and JPEG2000 decoding using of side information. The third stage converse the Dc equalization procedure followed by decimation in time domain which is reverse of interpolation of row/periods of 2D ECG array. The fifth stage of the reconstruction process is R peak based incorporation and estimation of raw ECG data.

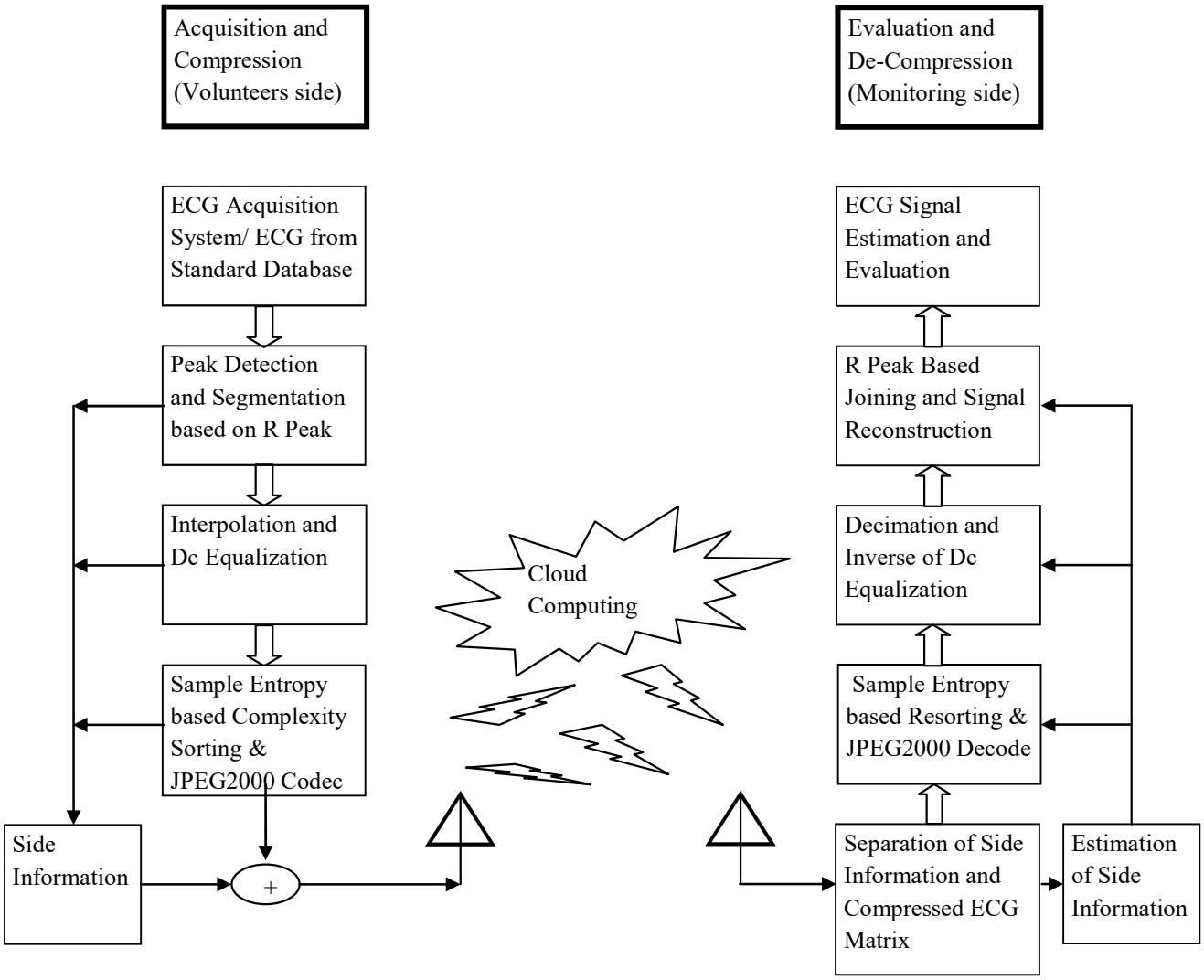


Fig. 2. Flow diagram of proposed ECG compression and decompression technique

4.1 R-Peak Detection, Segmentation and 2D ECG Array Formation

The peaks of QRS complex were detected to identify each RR interval and to map 1D ECG signal to 2D ECG array. Many QRS detection algorithms [1], [34], [35] have been proposed in literature and in the present work, the RR interval time series were estimated by the Tompkins method proposed in [32] for its simple implementation and high detection accuracy. The Fig. 3 has been depicts R-peak marking for the relatively irregular window segment taken from record 119 (for a total of 3000 samples) with varying period.

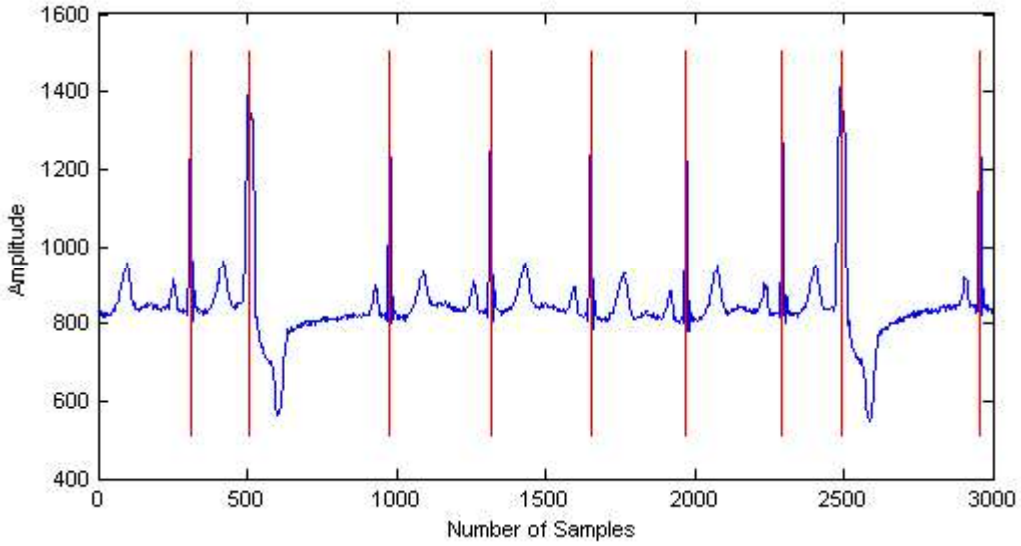


Fig. 3. R peak detection and marking for record 119 with varying period by Tompkins method

The segmentation and reassembling of ECG signal as a 2D array were accomplished by choosing R peak as its delineation boundary, leaving half peak at each end to the row. Further the row oriented assembly was performed by retaining the ECG samples from one R-peak to the next R-peak. The Fig. 4(a) shows the result of the 2D array of a row wise stacking, for the record of 117m from MIT-BIH arrhythmia ECG database.

4.2 Interpolation and Dc Equalization

The physiological and pathological alteration on patient's condition results in a left aligned segmented array (Fig. 4(a)) as they do not have equal period length in each heart beat segment. To form the equal universal period length of all periods and to better exploit the inter beat dependencies, period normalization was performed as proposed in [24] and adopted by [21]. The size of the original period lengths, original sequence of rows before sorting will be sent as side information along with the compressed file. As this information is sufficient to reconstruct the Dc equalized ECG image at the decompression side. Cubic spline interpolation was employed based on the maximum length of heart beat segment of 2D ECG array [21]. The interpolated array, for the record, of 117m from MIT-BIH arrhythmia ECG database is shown in Fig. 4(b).

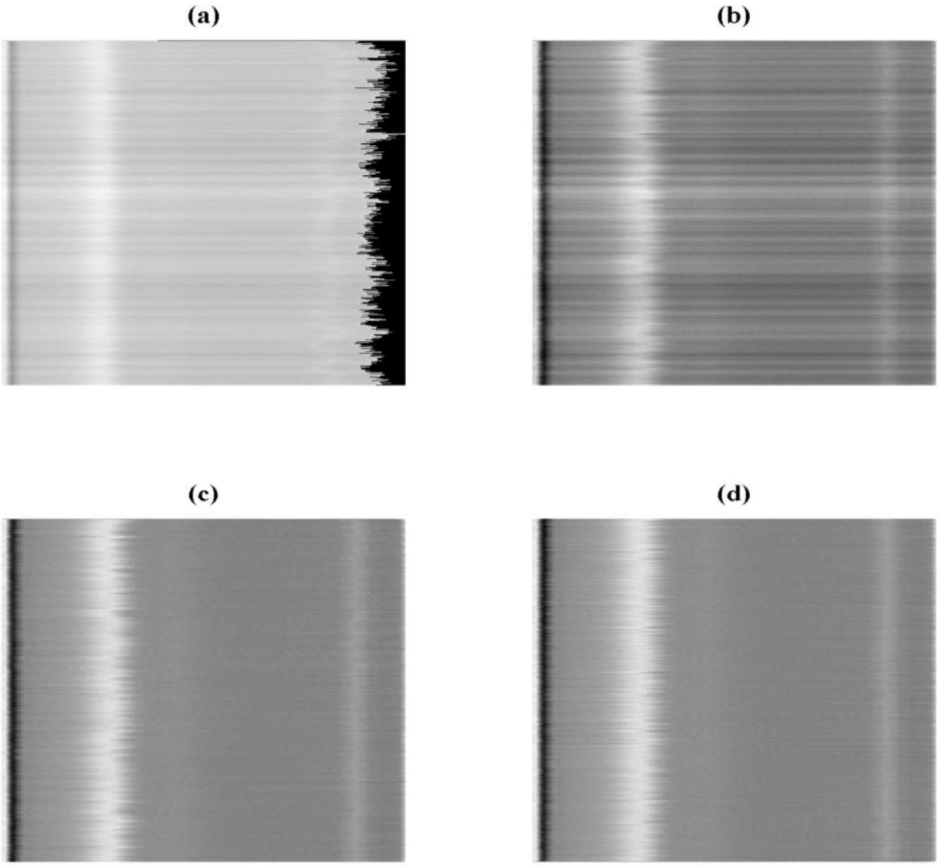


Fig. 4. Illustrations of the 2D ECG array of 117 with dimension (505×464) resulting from the proposed approaches (a) originally detected QRS peaks based segmented array (b) Row wise normalized (c) Dc equalized (d) Sample entropy based sorting applied to (c).

The adjacent lines of length normalized 2D ECG array may have different Dc levels that create high frequencies in vertical direction that deteriorate the performance of compressors. To counteract with this limitation all the periods are clamped to a minimum possible Dc level from original Dc levels of all periods.

$$dc_k = mean(x_k) \tag{11}$$

Where x_k are signal samples of k^{th} normalized period and dc_k is the average of all the signal samples averaged over the normalized length. Based on dc_k, minimum Dc level and an offset, all the segments are clamped to the minimum Dc level [21]. The process of Dc equalization results in a smoother 2D ECG matrix through reduction of vertical high frequency content. The size of the original offset, minimum Dc level and offset introduced were incorporated into the side information.

4.3 Sample Entropy based Complexity Sorting

Although the Dc equalization clamping reduces the vertical high frequency contents of resulting 2D ECG array (Fig. 4(c)), but the row wise adjacent periods are still being very dissimilar, which tends to diminish the compressor efficiency. In order to address this problem period sorting [22] and variance based complexity sorting [21] approaches are available in literature, but it still fails to guarantee the maximum similarity between the adjacent periods. The main contribution of this paper is to exploit a similarity among periods more efficiently by SampEn based complexity sorting.

After the interpolation and Dc equalization, the SampEn of all periods is computed, and the row with the smallest entropy is moved to the first index of the 2D ECG array. The other segments are then occupied by the remaining rows in ascending order of randomness. All this results in vertical smoothing of the formulated 2D ECG array.

4.3.1 SampEn

The SampEn is modified ApEn, which avoids the self-comparison [26], [36], [37]. The algorithm for SampEn is summarized as below

Given a signal $u(1),u(2),...u(N)$, where, N is the total number of data points. Fix m, a positive integer and r, a positive real number. For our study we have choose r equal to 20% of standard deviation and $m = 2$. SampEn algorithm [26], [37] can be summarized as

Step 1: Form *X(1)* to *X(N-m+1)* vectors defined as length of m

$$X(i) = [u_i\, u_{i+1} ... u_{i+m-1}] \quad 1 \le i \le N-m+1$$

Step 2: Calculation of distance between two vector d_m

$$d_m[X(i), X(j)] = max\left|u_{i+k-1} - u_{j+k-1}\right| \qquad k = 1, 2, ...m$$

Step 3: Calculation of number of similar segments in two vector

$$n_m(i) = d_m[X(i), X(j)] \le r \quad for \;\; i \ne j$$
$$n_{m+1}(i) = d_{m+1}[X(i), X(j)] \le r \quad for \;\; i \ne j$$

Step 4: Calculation of similarity measure of these segments $A_i^m(r)$, $B_i^m(r)$

$$B_i^m(r) = \frac{n_m(i)}{N-m+1}$$

$$A_i^m(r) = \frac{n_{m+1}(i)}{N-m+1}$$

Step 5: Calculation of mean measure of similar signal segments

$$B^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^m(r)$$

$$A^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} A_i^m(r)$$

Step 6: Calculation of Sample Entropy (*SampEn*) a finite data length of N can be estimated as

$$SampEn = -ln\left(\frac{A^m(r)}{B^m(r)}\right)$$

4.4 JPEG2000 Encoding

JPEG2000 by MATLAB 2012a software tool has been successfully employed as an image compression standard due to its ability to simultaneously address the need of progressive transmission by quality and spatial locality [33], [38]. The quantization step was fixed at a value of 1.5259×10^{-05}. Default parameters of JPEG 2000 were employed with the targeted CR.

Furthermore, in our proposed method, side information has been inserted to the compressed data via lossless encoding mechanism. Typical for record 100, the ECG matrix and side information size are quoted below.

1) Size of the 2-D ECG matrix (760×358)
2) Total side information (760×3)
    i) Original ECG beat ordering before complexity sorting (760×1)
    ii) Original Dc level for different ECG beat (760×1)
    iii) Original length of each period (760×1)

4.5 Reconstruction Procedure

The reconstruction of raw ECG data from the compressed file is accomplished by following inverse operation of compression stages shown in right half of Fig. 2. The first stage of restoration procedure was to separate and estimate the side information and compressed ECG array from the received file followed by second stage, i.e. inverse procedure of complexity sorting (reordering). The third stage reverses two basic compression steps, first is the inverse of Dc equalization and secondly decimation in order to recover time signal using spline decimation and finally the estimated ECG signal is available for cardiac analysis.

5. Experimental Results and Discussion

To evaluate the efficiency of the proposed preprocessing algorithm, all the 48 MIT-BIH Arrhythmia database ECG records have been considered for the experimentation. The visual analysis

has been depicted for typical 100, 117 and 119 records and same has been tabulated. These records have been chosen because validation results for them are available within the literature [21], [22]. It is implicitly assumed that the ECG reconstructed signals have been evaluated through visual inspection by the cardiologist. Therefore, for visual assessment of the proposed method, the original, reconstructed and error signals are shown in Fig. 5 to Fig. 7 for first 3000 samples of these records.

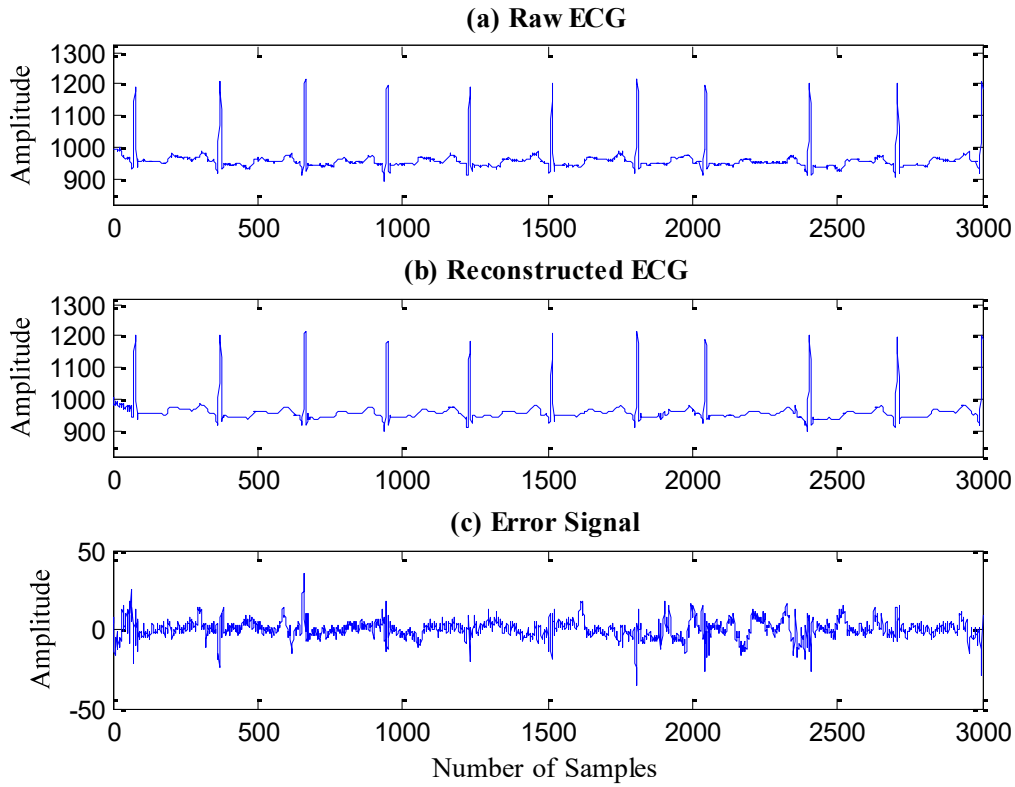


Fig. 5. (a) Original ECG from MIT-BIH database of record 100, (b) reconstructed ECG signal and (c) reconstruction error signal

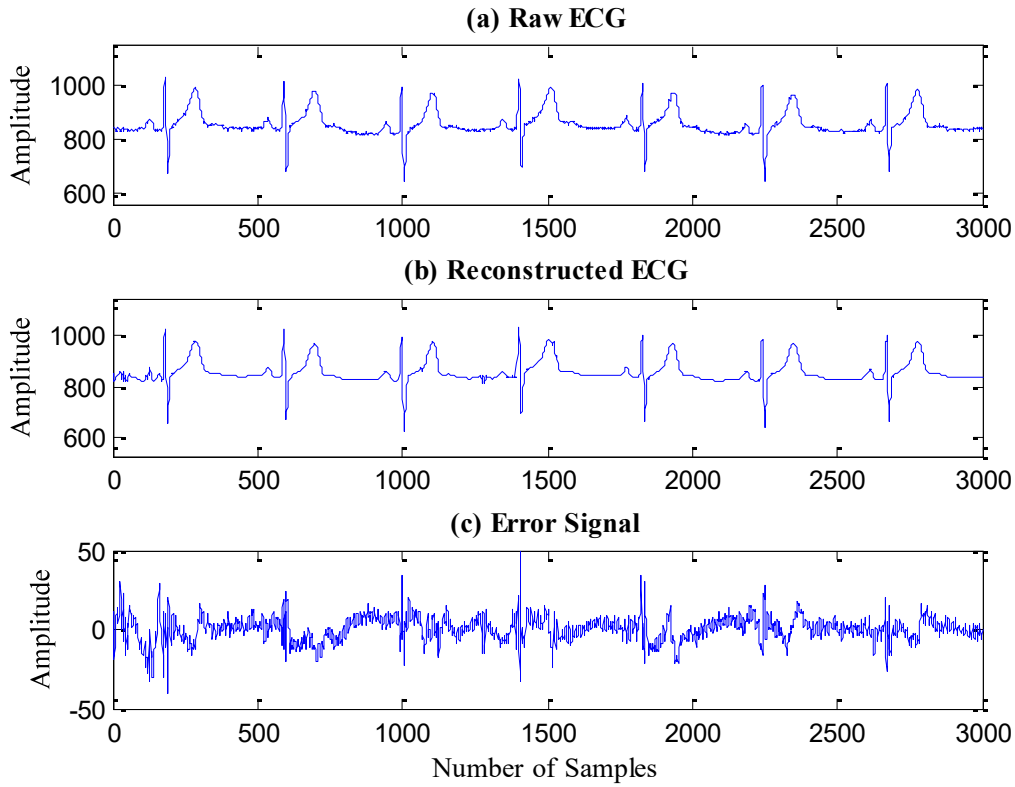


Fig. 6. (a) Original ECG from MIT-BIH database of record 117, (b) reconstructed ECG signal and (c) reconstruction error signal

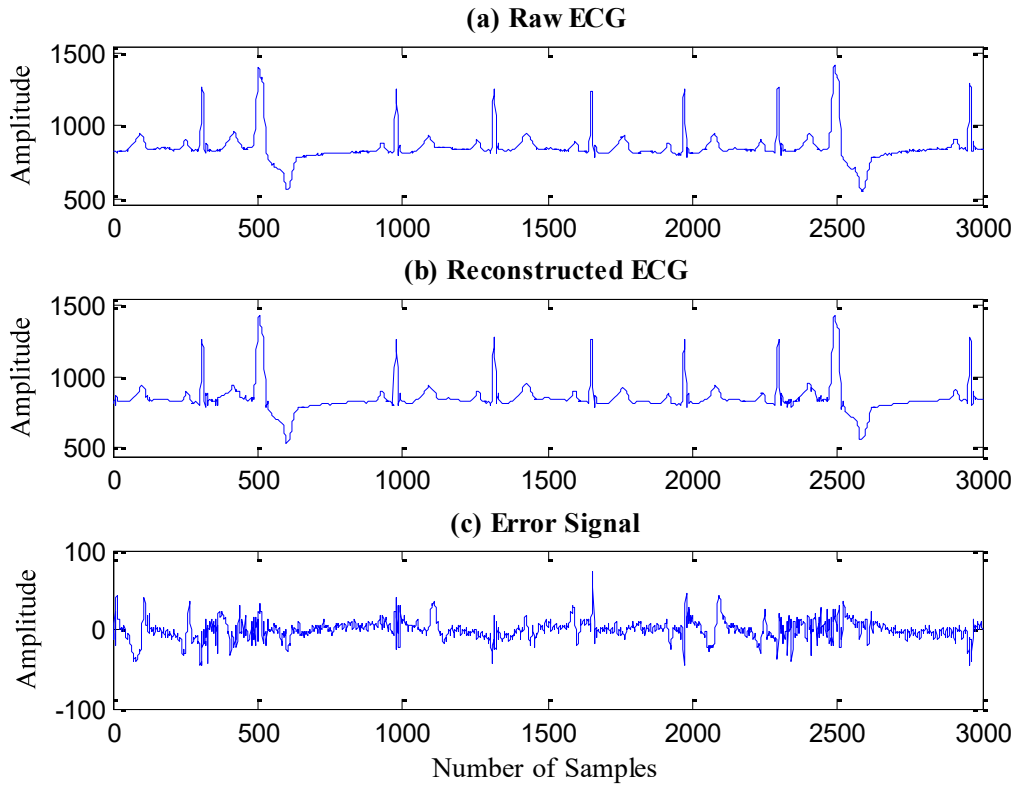


Fig. 7. (a) Original ECG from MIT-BIH database of record 119, (b) reconstructed ECG signal and (c) reconstruction error signal

The records 100, 117, and 119 were converted into matrices with dimensions 760×358, 505×464, and 659×506, respectively. Table 1 and 2 provides the performance evaluation for 48 records at short-term (10 minutes) and long-term (30 minutes) ECG data. The Tables gives insight of the efficiency while taking into consideration all the prevalent performance estimators. The QS_{PRD}, QS_{PRDN}, and $QS_{PRD1024}$ for both durations clearly justifies its efficacy for long window length records thereby capturing the non-linear characteristics of these signals.

For the fair comparison using the existing performance metrics i.e. PRD, PRDN and PRD1024 the results have been separately presented in different Table 3, 4 and 5. The respective QS has been measured using the different versions of the PRD, and the ratio has been tabulated.

Table 1 Performance measures of proposed technique for 48 ECG records from MIT-BIH arrhythmia database for 10 mins.

Record	CR	PRD	PRDN	PRD1024	RMS	SNR	QS_{PRD}	QS_{PRDN}	$QS_{PRD1024}$
100	55.50	0.55	14.89	7.29	5.33	16.54	100.07	3.75	7.62
101	58.57	1.78	29.32	11.45	17.22	10.66	32.95	3.69	5.08
102	58.85	1.09	27.74	18.88	10.65	11.14	53.80	1.90	3.16
103	60.18	0.66	10.16	7.94	6.49	19.86	90.91	6.16	7.61
104	58.68	2.21	37.92	43.40	21.61	8.42	26.61	0.86	1.10
105	48.63	0.69	10.68	8.77	6.74	19.43	70.88	4.53	5.52
106	50.83	1.88	26.92	24.17	18.62	11.40	27.07	1.87	2.10
107	61.14	2.97	17.71	17.12	29.40	15.03	20.61	3.45	3.59
108	58.63	1.98	46.22	24.92	19.42	6.70	29.56	1.31	1.94
109	52.14	0.84	9.50	7.63	8.23	20.44	62.18	4.89	5.55
111	59.54	1.05	20.40	17.33	10.44	13.81	56.71	2.87	3.37
112	57.17	0.65	12.12	3.27	5.59	18.33	87.73	4.67	17.53
113	62.30	1.58	17.83	16.75	15.69	14.98	39.54	3.53	3.76
114	64.35	1.80	59.41	41.77	17.86	4.52	35.77	1.71	2.39
115	58.70	1.01	13.32	7.74	9.35	17.51	58.23	4.34	7.51
116	50.84	1.81	12.04	6.24	15.29	18.39	28.04	4.48	8.06
117	71.48	0.73	13.10	3.25	6.26	17.66	97.85	5.98	21.98
118	45.17	3.96	38.65	17.91	33.96	8.26	11.40	1.17	2.57
119	52.24	1.19	9.59	4.23	10.22	20.36	43.92	6.59	12.45
121	66.40	0.80	12.68	4.02	6.87	17.94	83.34	5.15	16.35
122	52.64	0.77	9.050	3.62	6.64	20.87	67.99	5.75	14.49
123	66.15	3.81	55.58	19.27	32.94	5.10	17.38	1.18	3.42
124	68.32	1.79	14.15	7.72	15.57	16.98	38.10	4.92	8.77
200	42.69	2.62	35.24	29.21	26.32	9.06	16.27	1.30	1.37
201	47.98	1.14	30.33	20.71	11.30	10.36	42.03	1.69	2.29
202	61.76	2.58	53.36	39.97	25.59	5.46	23.91	1.28	1.57
203	37.76	3.68	34.46	43.48	36.58	9.25	10.26	0.77	0.81
205	46.46	0.47	11.72	10.02	4.48	18.62	99.64	2.31	4.54
207	43.66	3.76	44.05	44.10	37.41	7.12	11.61	1.01	1.08
208	41.99	2.56	27.40	43.42	25.52	11.24	16.40	0.80	0.84
209	46.66	1.11	21.32	18.00	11.04	13.42	41.93	2.19	2.60
210	44.51	0.89	17.44	36.65	8.86	15.17	49.90	0.92	1.09
212	52.36	1.57	23.68	21.82	15.67	12.51	33.27	2.18	2.41
213	46.71	2.51	18.86	16.42	24.61	14.49	18.57	2.64	2.86
214	44.81	4.35	47.43	49.45	43.40	6.48	10.30	0.87	0.91
215	39.94	1.17	20.78	18.67	11.65	13.65	34.17	1.90	2.14
217	57.54	2.37	19.62	15.44	23.64	14.15	24.31	3.02	3.12
219	48.05	4.58	43.21	26.30	41.56	7.29	10.49	1.13	1.82
220	56.04	0.92	13.43	6.35	8.45	17.44	60.68	4.33	8.81

Record	CR	PRD	PRDN	PRD1024	RMS	SNR	QS_{PRD}	QS_{PRDN}	$QS_{PRD1024}$
221	42.05	2.73	43.89	38.65	27.10	7.15	15.42	0.97	1.09
222	47.28	0.85	28.17	19.13	8.45	11.01	55.56	1.69	2.46
223	45.25	1.02	12.79	15.57	9.40	17.86	44.50	1.53	2.64
228	47.38	2.98	39.84	39.44	29.74	7.99	15.90	1.17	1.26
230	56.09	1.40	20.20	17.97	13.94	13.89	39.94	2.80	3.12
231	110.99	4.12	71.05	58.90	40.67	2.97	26.93	1.55	1.87
232	94.57	1.78	59.46	42.07	17.76	4.52	53.04	1.54	2.13
233	42.43	3.0	27.27	14.80	29.94	11.29	14.15	2.28	2.37
234	54.88	0.70	10.06	9.06	6.97	19.95	78.30	5.55	6.09

Table 2 Performance measures of proposed technique for 48 ECG records from MIT-BIH arrhythmia database for 30 mins.

Record	CR	PRD	PRDN	PRD1024	RMS	SNR	QS_{PRD}	QS_{PRDN}	$QS_{PRD1024}$
100	52.28	7.26	0.55	13.61	5.26	17.32	95.81	7.2	3.84
101	60.43	9.45	0.75	13.97	7.3	17.1	80.18	6.39	4.33
102	61.62	15.65	1	25.54	9.73	11.86	61.78	3.94	2.41
103	52.4	8.38	0.68	10.32	6.64	19.73	77.26	6.25	5.08
104	47.34	37.1	2.55	49.84	24.96	6.05	18.59	1.28	0.95
105	43.66	24.37	2.3	27.95	22.54	11.07	19.02	1.79	1.56
106	50.35	46.38	3.82	51.5	37.9	5.76	13.17	1.09	0.98
107	48.22	40.65	7.28	42.12	72.25	7.51	6.62	1.19	1.14
108	53.97	29.8	2.28	37.67	22.38	8.48	23.63	1.81	1.43
109	40.41	6.02	0.67	6.64	6.61	23.56	60.09	6.71	6.09
111	49.68	41.44	2.55	49.05	25.28	6.19	19.51	1.2	1.01
112	51.87	3.11	0.62	11.84	5.3	18.53	84.29	16.69	4.38
113	58.99	15.06	1.33	16.1	13.28	15.86	44.24	3.92	3.66
114	75.2	40.08	1.75	57.97	17.41	4.74	42.91	1.88	1.3
115	56.37	7.79	1.02	13.03	9.47	17.7	55.34	7.24	4.33
116	48.5	12.67	3.44	22.25	29.1	13.05	14.09	3.83	2.18
117	72.52	3.36	0.7	12.45	5.95	18.1	104.23	21.59	5.83
118	45.13	26.25	5.88	58.87	50.36	4.6	7.67	1.72	0.77

Record	CR	PRD	PRDN	PRD1024	RMS	SNR	QS_{PRD}	QS_{PRDN}	$QS_{PRD1024}$
119	52.32	5.05	1.19	9.56	10.25	20.39	43.82	10.36	5.47
121	55.17	4.35	0.86	13.01	7.44	17.71	64.08	12.68	4.24
122	54.76	3.31	0.71	8.31	6.08	21.60	77.28	16.55	6.59
123	66.9	20.41	3.99	59.58	34.61	4.50	16.75	3.28	1.12
124	64.65	20.14	4.33	40.55	37.55	7.84	14.93	3.21	1.59
200	40.03	17.91	1.4	18.58	14.12	14.62	28.51	2.24	2.15
201	59.51	36.59	1.86	47.59	18.49	6.45	31.95	1.63	1.25
202	49.35	44.41	3.06	51.09	30.35	5.83	16.13	1.11	0.97
203	35.42	41.35	4.36	43.74	43.35	7.18	8.13	0.86	0.81
205	41.67	16.96	1.28	31.31	12.33	10.09	32.57	2.46	1.33
207	46.75	44.77	3.55	49.78	35.23	6.06	13.17	1.04	0.94
208	36.14	40.57	4.13	43.01	41.13	7.33	8.74	0.89	0.84
209	47.22	17.49	1.11	20.54	11.01	13.75	42.58	2.7	2.3
210	39.76	43.35	2.66	50.57	26.43	5.92	14.95	0.92	0.79
212	48.1	18.34	1.35	20.26	13.41	13.87	35.7	2.62	2.37
213	37.91	12.52	1.79	13.19	17.71	17.6	21.17	3.03	2.88
214	45.46	52.36	5.23	55.34	52.12	5.14	8.69	0.87	0.82
215	36.97	12.41	0.8	14.09	7.95	17.02	46.29	2.98	2.62
217	48.08	41.32	5.25	42.83	52.38	7.36	9.16	1.16	1.12
219	50.18	30.23	5.34	44.19	48.77	7.09	9.39	1.66	1.14
220	59.11	7.01	0.96	13.81	8.8	17.19	61.69	8.43	4.28
221	42.19	43.45	3	49.44	29.79	6.12	14.07	0.97	0.85
222	42.41	34.87	1.7	45.58	16.92	6.82	24.9	1.22	0.93
223	39.25	25.88	3.66	41.57	33.84	7.63	10.73	1.52	0.94
228	50.93	39.24	2.94	42.27	29.34	7.48	17.33	1.3	1.2
230	56.04	21.43	1.7	23.77	16.84	12.48	33.04	2.62	2.36
231	102.26	54.73	3.44	63.88	34.14	3.89	29.75	1.87	1.6
232	84.44	39.2	1.82	55.65	18.01	5.09	46.51	2.15	1.52
233	34.84	17.16	1.94	17.82	19.39	14.98	17.96	2.03	1.95
234	39.35	7.38	0.55	8.17	5.51	21.76	70.94	5.34	4.82

Table 3 Performance comparison of proposed method with different compression techniques on some normal and abnormal ECG records having measure CR, PRD and. QS_{PRD} (- performance measure values not available for particular record in literature)

Data	DCT-based scheme [13]			Fractal based [39]			Cloud enabled fractal based [40]			Proposed		
	CR	PRD	QS_{PRD}	CR	PRD	QS_{PRD}	CR	PRD	QS_{PRD}	CR	PRD	QS_{PRD}
100	22.94	1.95	11.76	11.06	13.79	0.80	42	0.79	53.16	55.50	0.55	100.91
102	25.9	1.39	18.63	10.17	14.2	0.72	42	1.00	42.00	58.85	1.09	53.99
103	20.33	2.50	8.13	11.00	13.78	0.80	42	2.29	18.34	60.18	0.66	91.18
104	22.94	1.67	13.74	11.20	13.00	0.86	42	0.96	43.75	58.68	2.21	26.55
105	20.96	1.17	17.91	12.00	15.13	0.79	42	1.24	33.87	48.63	0.69	70.48
106	19.55	1.77	11.05	-	-	-	42	1.65	25.45	50.83	1.88	27.04
107	18.55	3.93	4.72	-	-	-	42	2.66	15.79	61.14	2.97	20.59
108	23.11	0.77	30.01	8.22	15.42	0.53	42	0.53	79.25	58.63	1.98	29.61
109	19.89	0.76	26.17	11.00	17.39	0.63	42	0.87	48.28	52.14	0.84	62.07
111	22.99	1.03	22.32	-	-	-	42	0.92	45.65	59.54	1.05	56.70
112	23.82	1.00	23.82	-	-	-	42	1.18	35.59	57.17	0.65	87.95
113	19.96	2.89	6.91	-	-	-	42	2.40	17.50	62.30	1.58	39.43
114	25.58	1.08	23.69	-	-	-	42	0.87	48.28	64.35	1.80	35.75
117	24.00	1.17	20.51	4.50	14.64	0.31	42	1.45	28.97	71.48	0.73	97.92
119	19.00	2.05	9.27	-	-	-	42	1.50	28.00	52.24	1.19	43.90

Table 4 Performance comparison of proposed method with different compression techniques on some normal and abnormal ECG records having measure CR, PRD1024 and. $QS_{PRD1024}$ (P PRD1024 and Q* QSPRD1024)*

Data	Dc equalization and complexity sorting [21]			Mean extension and period normalization [22]						Proposed		
				Approach 1			Approach 2					
	CR	P*	Q*	CR	P*	Q*	CR	P*	Q*	CR	P*	Q*
100	24	3.95	6.07	24	5.21	4.61	24	4.06	5.91	27.75	3.645	7.61
117	24	1.72	13.95	10	0.98	10.2	13	1.18	11.02	35.74	1.625	21.99
119	20	1.92	10.42	21.6	2.81	7.69	20.9	2.81	7.47	26.12	2.115	12.35

Table 5 Performance comparison of proposed method with different compression techniques on some normal and abnormal ECG records having measure CR, PRDN and. QS_{PRDN}

Data	DCT-based scheme [13]			Adaptive Fourier decomposition [41]			Natural basis k-coefficients via sparse decomposition [42]			Proposed		
	CR	PRDN	QS_{PRDN}	CR	PRDN	QS_{PRDN}	CR	PRDN	QS_{PRDN}	CR	PRDN	QS_{PRDN}
100	22.94	48.88	0.47	25.64	16.18	1.58	78.20	18.03	4.34	55.50	14.89	3.73
101	23.86	38.34	0.62	25.64	12.87	1.99	80.24	14.66	5.47	58.57	29.32	2.00
102	25.91	35.70	0.73	25.64	22.26	1.15	50.54	18.45	2.74	58.85	27.74	2.12
103	20.33	37.74	0.54	25.64	14.4	1.78	46.32	12.57	3.68	60.18	10.16	5.92
109	19.89	8.05	2.47	25.64	15.73	1.63	24.86	13.70	1.81	52.14	9.50	5.49
111	22.99	19.60	1.17	25.64	19.45	1.32	31.05	26.20	1.19	59.54	20.40	2.92
112	23.82	19.08	1.25	25.64	18.73	1.37	34.06	16.58	2.05	57.17	12.12	4.72
113	19.96	34.85	0.57	25.64	6.85	3.74	37.42	14.08	2.66	62.30	17.83	3.49
115	19.88	38.00	0.52	25.64	11.84	2.17	38.26	9.76	3.92	58.70	13.32	4.41
117	24.43	20.80	1.17	25.64	11.23	2.28	38.94	14.42	2.70	71.48	13.10	5.46
119	19.31	16.30	1.18	25.64	10.77	2.38	16.26	32.19	0.51	52.24	9.59	5.45
121	25.84	7.73	3.34	25.64	9.92	2.58	26.67	17.36	1.54	66.4	12.68	5.24

Table 3 gives the performance comparison with recent works based on DCT [13], Fractal [39] and Cloud enabled fractal [40] method. For a typical record 119, QSPRD is 43.90. Similarly, Table 4 provides the algorithm assessment using PRD1024 metric. The QSPRD1024 for record 119 is 12.35. Lastly, Table 5 provides the analysis using PRDN measure. Comparison with the recent works in [13], [41] and [42] gives the performance improvement in QS_{PRDN} is 4.27, 3.07,4.94 using the proposed scheme for record 119.

The advantage of the proposed method is its superior CR, PRD and QS performance. It is in agreement with the wide consensus "QS is a best performance indicator while taking into consideration the both aspect reconstruction distortions (PRD) as well as a quantitative description of the compression (CR)". The proposed method performs excellently by obtaining better QS as compared with other methods for all versions of PRD.

From the formulated results on different ECG databases in Table 6, it can be concluded that values of CR, PRD and QS_{PRD} for various lossy, lossless and tends to lossless methods outperformed in respect to the proposed method. The novelty in the compression side from previous work [21] has been achieved by replacing variance based sorting with SampEn based complexity sorting mechanism. It achieves self-similarity among the vertical columns of 2D ECG matrix. At the reconstruction end, any desired ECG beat can be extracted via an appropriate selection of complexity sorted ECG beat number along with the other side information. This beat number results in the customizable retrieval of beats. It does not necessarily reduce the overall decompression time but

provide access to the selective ECG data segments. Fig. 8 gives an extensive analysis for different durations of the ECG records. From the graphical analysis, it is seen that the algorithm works well for varying range of time durations.

Table 6 Performance comparison of proposed technique for average values for database (MIT-BIH Arrhythmia database, ** mean ± standard deviation)*

Algorithm	**Database**	**PRD**	**CR**	**QS_{PRD}**
m-AZTEC [5]	CSE	25.5	5.6	0.22
Perceptual Masks [14]	*	1.24	3.5	2.82
SPIHT [15]	*	1.18	8	6.78
Linear prediction with wavelet [20]	*	5.3	11.6	2.19
ASCII encoding [7]	PTB [43]	0.023	7.18	312.17
ASCII encoding and transmission[8]	PTB [43]	7.89	15.72	1.99
Wavelet and vector quantization [23]	*	1.6 ± 0.98**	12	5.00
JPEG2000 [38]	*	3.26	20	6.13
Hilton [44]	*	2.6	8	3.08
Discrete symmetric wavelet transform [45]	*	3.9	8	2.05
Neural networks [46]	*	0.61	12.74	20.89
Proposed	*	**1.88**	**54.96**	**29.23**

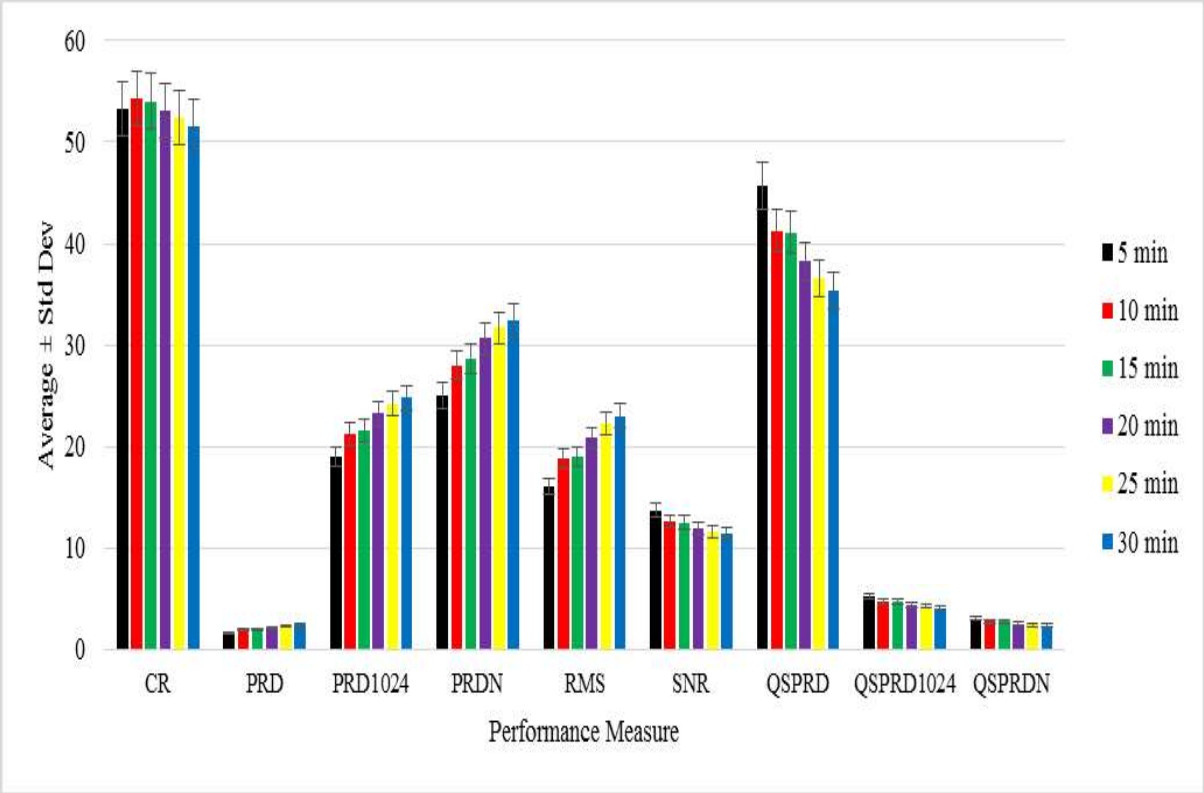


Fig. 8. Average and standard deviation values of different performance metrics at varying ECG time durations

The step by step result enhancement trend has been depicted in Table 7 for particular record 117. The Table shows an increase in QS after each intermediate step. The combination that resulted in best QS is the third one. Undoubtedly the major contribution for this increase is because of the sample entropy based complexity sorting scheme.

Table 7 Step-by-step performance enhancement trend for particular record 117 of proposed method

Algorithm Steps	QS	QS_{1024}	QS_N	Trend
After Period Normalization	13.05	2.67	0.73	-
After Period Normalization + Dc Equalization	58.94	12.07	3.29	↑
After Period Normalization + Dc Equalization + Sample Entropy Based Complexity Sorting	107.32	21.98	5.98	↑

6. Conclusion

The main conclusion of this paper is the modified pre-processing algorithm for compression of quasi-periodic ECG signals. This algorithm results in minimum loss of information by applying SampEn based nonlinear complexity sorting mechanism in addition to period normalization and Dc equalization in 2D ECG array/matrix. By use of this pre-processing approach along with JPEG2000 encoder, it outperformed other methods by achieving QS equal to 41.24, 4.73, and 2.75 at different

values of reconstruction error namely PRD, PRD1024 and PRDN. The results reveal that it would be worthwhile to develop a more efficient method that would adapt minimization reconstruction error due to period normalization. The modified pre-processing for quasi-periodic ECG as represented by an image is a useful and powerful method to achieve higher compression at low reconstruction error

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