

## Chapter 2

# Quantification of Diagnostic Information from Electrocardiogram Signal: A Review

S. Dandapat, L.N. Sharma and R.K. Tripathy

**Abstract** Electrocardiogram (ECG) contains the information about the contraction and relaxation of heart chambers. This diagnostic information will change due to various cardiovascular diseases. This information is used by a cardiologist for accurate detection of various life-threatening cardiac disorders. ECG signals are subjected to number of processing, for computer aided detection and localization of cardiovascular diseases. These processing schemes are categorized as filtering, synthesis, compression and transmission. Quantifying diagnostic information from an ECG signal in an efficient way, is always a challenging task in the area of signal processing. This paper presents a review on state-of-art diagnostic information extraction approaches and their applications in various ECG signal processing schemes such as quality assessment and cardiac disease detection. Then, a new diagnostic measure for multilead ECG (MECG) is proposed. The proposed diagnostic measure (MSD) is defined as the difference between multivariate sample entropy values for original and processed MECG signals. The MSD measure is evaluated over MECG compression framework. Experiments are conducted over both normal and pathological MECG from PTB database. The results demonstrate that the proposed MSD measure is effective in quantifying diagnostic information in MECG. The MSD measure is also compare with other measures such as WEDD, PRD and RMSE.

**Keywords** Diagnostic measure · Multichannel ECG · Multivariate sample entropy · MSD · PRD · WEDD

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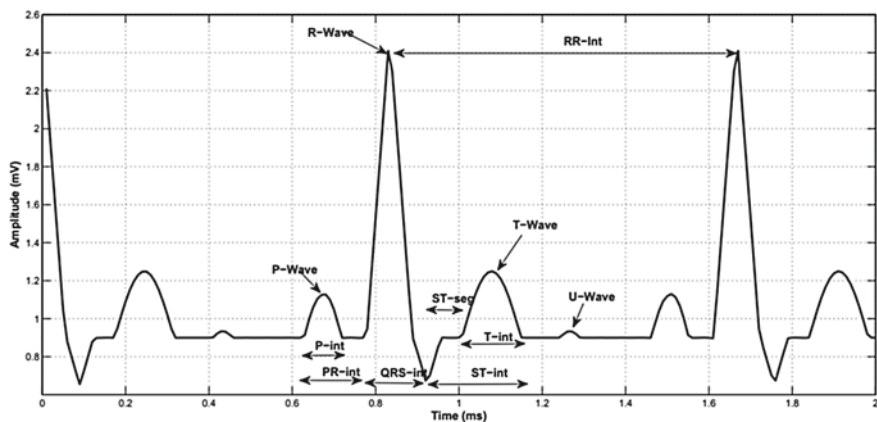
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## 2.1 Introduction

The cardiovascular system (CVS) consists of heart and blood vessels [1]. The function of heart is to provide oxygenated blood to whole body. The electrical activity of the heart is coordinated by pacemaker cells. Pacemaker cells are specialized cardiac myocytes [2]. These cells are having its own intrinsic peaks or firing rate. In heart, each cell can act as pacemaker. Due to firing rate, there are four major kind of pacemaker cells, that are responsible for electrical conduction in heart [2, 3]. These are categorized as sino-atrial (SA) node, atrio-ventricular (AV) node, HIS bundle and purkinje fibers. The firing of SA node, leads to atrial depolarization. After a delay, the AV node fires and these intrinsic peaks act as intermediate to bring the electrical activity from the upper chamber to lower chamber of heart. The HIS bundle and purkinje fibers responsible for depolarization of the septum and the ventricles. The re-polarization of myocardium is occurred after depolarization in the opposite direction. The bio-electrical activity of entire heart is measured through ECG [1, 2, 4]. Each heart beats in ECG consist of diagnostic features such as waveform amplitude and interval. Figure 2.1 shows the synthetic ECG marked with the diagnostic features. These features are examined by a cardiologist for accurate detection and localization of cardiac disorders. The detail description of each of these morphological diagnostic features are given as [1, 2].

- P Wave:** It is a low amplitude clinical component present in ECG. The P-wave gives the information about both left and right atrial contraction. Due the atrial flutter and atrial fibrillation kind of cardiac arrhythmia the unordered nature of P-wave occurs with a very high rate [2].



**Fig. 2.1** Shows the synthetic ECG signal marked with morphological diagnostic features as waveform amplitude and interval [5]

- **QRS Complex:** This clinical component present in ECG is due to ventricular contraction. It is one of the important clinical feature for the evaluation of heart rate [2].
- **T Wave:** This waveform occurred in ECG due to ventricular relaxation. The shape of this waveform is one of the important characteristics to diagnose various cardiac arrhythmia. The shape of T-wave will change due to hyperkalemia, hypokalemia, hypercalcemia and myocardial infarction type of heart diseases [2].
- **PR Segment:** It is the time between the end of P-wave and the beginning of QRS complex. This component is a iso-electric line and mainly corresponds to the delay, after which the second pacemaker of heart (atrio-ventricular node) fires.
- **RR Interval:** In ECG the R-wave has highest amplitude among other clinical components. The difference between R-wave locations of consecutive beats is called as RR-interval. The RR-interval variation is one of the important feature for diagnosis respiratory disorder, sleep apnea etc. [2].
- **ST Segment:** This clinical component is due to the end of ventricular contraction and beginning of ventricular relaxation. The depression and elevation of ST-segment is the indicator of cardiac arrhythmia [2].
- **QT Interval:** This clinical component present in ECG is mainly due to the beginning of ventricular contraction and end of ventricular relaxation. The relationship between QT interval and RR interval is they are directly proportional. Due to tachycardia the heart rate is more this implies the QT interval shortens. Similarly, due to bradycardia the heart rate is less, and this results a longer QT interval [2].
- **U Wave:** This type of waveform seen in lead V2 and V3 and it is due to the delayed relaxation of purkinje fibers [1, 2]. It is present in ECG, when the heart rate falls below 60bpm [2].

The 12-lead or Multilead ECG (MECG) provides the spatial as well as temporal information about cardiac rhythm. It is widely used in hospitals for diagnosis of cardiac ailments [2]. These signals are recorded by placing 10 number of electrodes on the surface of body. The MECG consists of uni-polar limb lead, bipolar limb leads and precordial leads [6]. The unipolar and bipolar limb leads are derived from the potentials recorded through the electrodes placed at right leg (RL), left arm (LA) and right arm (RA) [2, 7]. The Anterior View (V1, V2, V3 and V4), Left lateral View (I, aVL, V5 and V6) and Inferior View (II, III and aVF) of heart is seen from MECG [2]. The cardiac ailments such as myocardial infarction, valvular disease, hypertrophy, myocarditis, bundle branch block, atrial flutter, atrial fibrillation, ventricular fibrillation, ventricular tachycardia and cardiomyopathy are detected from MECG [1, 2, 8]. The description of each of these cardiac arrhythmia are given below [2].

- **Sinus Bradycardia**—In this case all the beats in ECG are normal, RR-interval is more and heart rate (HR) < 60beats/min.
- **Sinus Tachycardia**—It is occurred due physiological stress or exercise. Here, all the beats are normal, RR-interval is less and HR > 100beats/min.
- **Sinus Arrhythmia**—The HR increases due to inspiration and decreases due to expiration. This type of arrhythmia particularly found in children [1].

- **Wandering Pacemaker**—In this type of arrhythmia the impulse is originated from various points of atria [1]. In ECG due to Wandering Pacemaker there is a variation in P-wave polarity, PR-interval, PP-interval and RR-interval.
- **Atrial Flutter**—In this case the end of T-wave and beginning of P-wave disappears, P-wave results in a circus movement inside atria with high rate of activation between 160 to 200 beats/min [1].
- **Atrial Fibrillation**—Impulse is having chaotic and random pathways in atria, Baseline and ventricular depolarization are irregular with high rate of activation between 250 to 300 beats/min [1].
- **Junctional Rhythm**—In this arrhythmia the impulse is originated at AV node, P-wave often inverted and may be under or after QRS complex [1].
- **Premature Ventricular Contraction**—In this case the origin of electrical conduction is in ventricular Muscle not the AV node, QRS-complex is abnormal and longer than 0.1 s [1].
- **Ventricular Tachycardia**—Slower conduction in ischemic ventricular muscle which leads to circular activation. this may cause a rapid, bizarre and wide QRS-complexes with a rate of 120 beats/min [2].
- **Ventricular Fibrillation**—Ventricular muscle contraction is irregular and ineffective of pumping blood. The ventricular fibrillation (VF) can be stops using external defibrillator [2].
- **Right Atrial Hypertrophy**—It is due to the consequence of right atrial overload, tricuspid valve disease and pulmonary valve disease [2]. Due to this arrhythmia the amplitude of P-wave is greater than 0.25 mv in Lead II, III and aVF.
- **Left Atrial Hypertrophy**—It is due to the consequence of right atrial overload and mitral valve disease [2]. A notched P-wave and biphasic p-wave seen in lead II lead V1 respectively with a negative amplitude  $>0.1$  mv.
- **Right Ventricular Hypertrophy**—It is the consequence of pulmonary valve stenosis and pulmonary hypertension [2]. In ECG, a tall R-wave seen in Lead V1 and V2 with amplitude  $>0.7$  mv, wide S-wave seen in lead V1 and V2, wide R-wave seen in V5 and V6.
- **Left Ventricular Hypertrophy**—It is the consequence of left atrial overload, mitral valve disease and aortic valve disease [2]. In MEEG a tall R-wave in lead I, V5, V6 and tall S-wave in lead III, V1 and V2 occurs.
- **Anterior Myocardial Infarction**—This type of MI is due to the occlusion in left anterior descending artery [2]. Due to anterior infarction, the R-wave progression occurred in precordial leads.
- **Inferior Myocardial Infarction**—This type of MI is due to the occlusion in right coronary artery [2]. Due to inferior infarction, the Q-wave variation occurred in lead II, III and aVF.
- **Posterior Myocardial Infarction**—This type of MI can be diagnosed by observing the reciprocal changes in the ECG at lead V1 [2].
- **Lateral Myocardial Infarction**—This type of MI is due to the occlusion in left circumflex artery [2]. The ST-segment elevation occurs in lead I, aVL, V5 and V6.

The pathological Q-wave formation in lead V6 is due to lateral myocardial Infarction.

- **Hyperkalemia**—This type of cardiac arrhythmia occurred due to the increase of potassium ion concentration in blood [2]. In ECG due to hyperkalemia a peaked T-wave and small p-wave occurs.
- **Hypokalemia**—Due to the decrease of potassium ion concentration in blood the flattened or inverted T waves, ST depression and a wide PR interval occurs [2]. These changes are due to the consequence of hypokalemia.

## 2.2 ECG Quality Assessment Techniques: A Review

ECG signals are subjected to different processing for storage, transmission and retrieval. The goal of distortion measures in ECG signal processing is to quantify the loss of clinical information. There are two kind of distortion measures are used to evaluate the quality of ECG signals [5]. These are subjective distortion measure and objective distortion measure. In the following subsections the state-of-art distortion measures and their limitations are briefly discussed.

### 2.2.1 Subjective Assessment

The subjective quality of ECG signals for clinical practice is evaluated by visual inspection of morphological diagnostic features [8, 9]. The researchers and medical experts judges the diagnostic quality of processed ECG signal by inspecting these morphological diagnostic features. After inspection they assigns a score to each of the morphological diagnostic feature. This score is defined as

$$MOS_l = \frac{\sum_{c=1}^{N_c} R_c}{N_c} \quad (2.1)$$

where  $N_c$  corresponds to number of experts involved for investigating the morphological diagnostic features.  $R_c$  is the quality rating or score for  $l$ th morphological diagnostic feature. The values of  $R_c$  are defined as 1-bad, 2-not bad, 3-good, 4-very good and 5-excellent. For a ECG signal the mean opinion score (MOS) is defined as the average of individual scores for  $l$ th morphological diagnostic feature. The MOS rating is defined by

$$MOS = \frac{\sum_{l=1}^{N_f} MOS_l}{N_f} \quad (2.2)$$

The percentage of difference between the MOS scores for original and processed ECG signal is defined as the subjective distortion measure. The error measures for

each morphological features are defined as

$$MOS_l^{err} = \frac{5 - MOS_l}{5} \times 100 \quad (2.3)$$

The  $MOS_l^{err}$  corresponds to the subjective error measure for  $l$ th morphological diagnostic feature. For  $MOS_l^{err}$  evaluation the MOS score for original ECG diagnostic features are assigned as excellent. The subjective distortion measures for ECG signal is defined as

$$MOS^{err} = \frac{5 - MOS}{5} \times 100 \quad (2.4)$$

The subjective tests are time taking and cumbersome processes. Due to this drawback, the researchers develop objective distortion measures. The objective measures are evaluated by comparing the diagnostic features in temporal and transformed domain for original and processed ECG signals. The objective measures are validated through subjective tests. There are two kinds of objective measures reported from literature. These are objective non-diagnostic and objective diagnostic measures.

### 2.2.2 Objective Non-diagnostic Distortion Measures

In this subsection, the non-diagnostic distortion measures, which are used to evaluate quality of processed ECG signals are discussed. The mean square error (MSE) is evaluated as the difference between the amplitude of original and the processed ECG signals [10]. The processed signals are obtained due to various ECG processing schemes as compression, transmission, enhancement and super-resolution ECG. Considering a discrete time signal given by  $x(n) = \{x(1), x(2), x(3), \dots, x(N)\}$ , which consists of  $N$  number of samples. The processed signal is given as  $\tilde{x}(n) = \{\tilde{x}(1), \tilde{x}(2), \tilde{x}(3), \dots, \tilde{x}(N)\}$ . The MSE between original and processed signal is expressed as

$$MSE = \frac{1}{N} \sum_{n=1}^N [x(n) - \tilde{x}(n)]^2 \quad (2.5)$$

In geometrical meaning, the MSE is defined as the euclidean distance between original and processed ECG signals. There are number of morphological diagnostic features embedded in ECG signal. Each of these features is having diagnostic importance. The MSE is only evaluated by considering the amplitudes, so for non-diagnosis regions (baseline in ECG) it exploits a large error. This large error make the processed ECG falls behind the clinical acceptable range. To overcome the drawbacks of MSE, the normalized mean square error (NMSE) is used [4]. This measure is given as

$$NMSE = \frac{\sum_{n=1}^N [x(n) - \tilde{x}(n)]^2}{\sum_{n=1}^N [x(n)]^2} \quad (2.6)$$

The normalization is used to make the error measure independent of the amplitudes of original ECG signal. As in ECG signal, the amplitudes are different for different leads and subjects. As NMSE measure is independent of the amplitude, so it is normally used as a good objective non-diagnostic distortion measures for various applications.

The root mean square error (RMSE) has been used to evaluate quality of ECG signals [11]. This measure is given as

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N [x(n) - \tilde{x}(n)]^2} \quad (2.7)$$

The RMSE fails to quantify the distortion in local diagnostic regions. The normalized root mean square error (NRMSE), is also used as objective diagnostic error measures in different applications. It is given as

$$NRMSE = \sqrt{\frac{\sum_{n=1}^N [x(n) - \tilde{x}(n)]^2}{\sum_{n=1}^N [x(n)]^2}} \quad (2.8)$$

The percentage root mean square differences (PRD) is used to evaluate quality of processed signal in almost all ECG compression and enhancement applications [12]. It is defined by

$$PRD1 = \sqrt{\frac{\sum_{n=1}^N [x(n) - \tilde{x}(n)]^2}{\sum_{n=1}^N [x(n)]^2}} \times 100 \quad (2.9)$$

where  $x(n)$ ,  $\tilde{x}(n)$  are the original and processed ECG signals. PRD2 is also used in various compression and enhancement techniques for evaluating the quality of processed signals. This measure is evaluated after subtracting the baseline of 1024 and mean value from the original ECG signal. The PRD2 is given as

$$PRD2 = \sqrt{\frac{\sum_{n=1}^N [x(n) - \tilde{x}(n)]^2}{\sum_{n=1}^N [x(n) - \mu_0 - 1024]^2}} \times 100 \quad (2.10)$$

where  $\mu_0$  corresponds to the mean value of the original ECG signal. In some applications, the PRD3 is also used to evaluate the objective quality of processed ECG signals. This PRD3 measure is given as

$$PRD3 = \sqrt{\frac{\sum_{n=1}^N [x(n) - \tilde{x}(n)]^2}{\sum_{n=1}^N [x(n) - 1024]^2}} \times 100 \quad (2.11)$$

The PRD1 value is found to lowest from PRD2 and PRD3 for evaluating the quality of processed ECG signal. The ECG signal with low PRD value not necessarily provide better diagnostic quality. For the ECG signal  $x(n)$  with fluctuating baseline, and high standard deviation, the PRD will be artificially lower [8]. The PRD and other similar type of error measures have the limitations to evaluate the diagnostic quality of ECG signals [9].

Signal to noise ratio (SNR) has been used as a objective non-diagnostic distortion measure to evaluate the performance of ECG compression technique [13]. This measure is given as

$$SNR = 10 \log_{10} \left( \frac{\sum_{n=1}^N [x(n) - \mu_0]^2}{\sum_{n=1}^N [x(n) - \tilde{x}(n)]^2} \right) \quad (2.12)$$

The SNR value is high at the high activity regions of interest as compared to other regions [9].

The normalized cross-correlation (NCC) measure has been used to evaluate the objective quality of ECG signals [14]. The NCC measure defines the similarity between original and processed ECG signals and it is given by

$$NCC = \frac{\frac{1}{N} \sum_{n=1}^N [x(n) - \mu_0] \sum_{n=1}^N [\tilde{x}(n) - \mu_r]}{\sqrt{\frac{1}{N} \sum_{n=1}^N [x(n) - \mu_0]^2} \sqrt{\frac{1}{N} \sum_{n=1}^N [\tilde{x}(n) - \mu_r]^2}} \quad (2.13)$$

The  $\mu_0$  and  $\mu_r$  corresponds to the mean values of both original signal and processed ECG signal. The NCC measure is used to find the similarity in local waves between original and processed ECG signal.

The percentage area difference (PAD) based objective non-diagnostic distortion measure has been used to evaluate the quality of ECG signal in [15]. This distortion measure is computed by considering the difference in the area enclosed between the original and the processed ECG signals. The PAD measure is given as

$$PAD = \frac{\left| \int_{t_i}^{t_f} y(t) - \int_{t_i}^{t_f} y_r(t) \right|}{(t_i - t_f)(y_{max} - y_{min})} \times 100 \quad (2.14)$$

The  $t_i$  and  $t_f$  corresponds to the initial and final time instants of the segment,  $y_{max}$  and  $y_{min}$  are the maximum and minimum values in the original ECG signal. The numerator term correspond to the absolute error in terms of area difference between the original and processed ECG signal. The denominator is used as a normalization factor for making the distortion measure independent of area.

The maximum amplitude error (MAX) has been used as a distortion measure in ECG compression technique [16]. This measure can quantify the local distortion in ECG signal. This measure is given as



$$\text{MAX}_i = \max_{n=1}^{N_{ci}} \{|x(n) - \tilde{x}(n)|\} \quad (2.15)$$

where,  $N_{ci}$  corresponds to number of samples in  $i$ th cycle.

Similarly, the normalized maximum amplitude error (NMAX) was used for quantifying distortion in [9]. This measure is given as

$$\text{NMAX}_i = \frac{\max_{n=1}^{N_{ci}} \{|x(n) - \tilde{x}(n)|\}}{\max_{n=1}^{N_{ci}} \{x(n)\} - \min_{n=1}^{N_{ci}} \{x(n)\}} \quad (2.16)$$

The normalization is done to make error independent of amplitude value. The average of NMAX measure for entire ECG signal is evaluated by averaging over all the cycles.

The objective non-diagnostic distortion measures have limitations to quantify the local distortions in the ECG signals. The Standard error (StdErr) has been used as objective non-diagnostic measure for evaluating the quality ECG signals [9]. The StdErr is given by

$$\text{StdErr} = \sqrt{\frac{1}{N_c - 1} \sum_{n=1}^{N_c} [x(n) - \tilde{x}(n)]^2} \quad (2.17)$$

$\text{StdErr}$  is similar to RMSE, where the denominator term is  $N_c$  instead of  $N_c - 1$ .

### 2.2.3 Objective Diagnostic Distortion Measures

Due to the drawbacks of non-diagnostic distortion measures for evaluating the quality of ECG signal, the objective diagnostic distortion measures are used. In this subsection, the objective diagnostic measures for ECG signals reported from literature are also briefly discussed.

Chen and Itoh proposed an objective diagnostic distortion measure for evaluating the quality of ECG signal [14]. The measure is the weighted PRD between clinical diagnostic features of original and processed ECG signals. It is given as

$$\text{WPRD} = \sqrt{\frac{\sum_{k=1}^M w_k \gamma_k}{\sigma}} \quad (2.18)$$

where  $w_k$  are the weights,  $\gamma_k$  is the MSE of clinical diagnostic features as P-wave, Q-wave, QRS-wave and ST-wave for original and processed ECG signals. The  $\sigma$  corresponds to the power of original ECG signal. The weights are assigned according to the clinical importance of diagnostic features. As per the example, the higher weight is given to ST-segment and T-wave and QRS amplitudes due to their importance in the diagnosis of cardiac arrhythmia.

Zigel and his group [17] proposed a objective diagnostic distortion measure for evaluating the quality of processed ECG signal. They extracted sixteen clinical morphological features from both original and processed ECG signals and define the distortion measure as:

$$WDD(\beta, \tilde{\beta}) = \Delta\beta^T \cdot \frac{w}{tr[w]} \cdot \Delta\beta \times 100 \quad (2.19)$$

where  $\beta, \tilde{\beta}$  corresponds to the clinical feature vectors corresponding to original and processed signal. The ‘ $w$ ’ corresponds to the weight value for the respective morphological features. The weights are assigned based on the diagnostic importance of the morphological features. The limitations of both WPRD and WDD measures are selection of optimal weights and identification of ‘ $PQRST$ ’ points for evaluating the diagnostic features in ECG signal.

The wavelet based distortion measures overcome the limitations in WPRD and WDD by assigning the weights through different parameters as energy and entropy. Al-Fahoum proposed an objective diagnostic distortion measure for evaluating the quality of compressed ECG signal [18]. In the wavelet domain, the clinical diagnostic features are captured through approximation and detail coefficients. The distortion measure is defined as the weighted percentage root mean square difference between the wavelet coefficients of original and processed ECG Signals.

$$WWPRD = \sum_{j=1}^{L+1} w_j WPRD_j \quad (2.20)$$

where,  $L$  corresponds to the number of decomposition levels,  $w_j$  corresponds to the weight of the  $j$ th subband and  $WPRD_j$  is the PRD value of the  $j$ th wavelet coefficients in the subband. In this measure the weights are computed as the ratio of sum of the absolute value of wavelet coefficients within that sub-band to the sum of absolute value of wavelet coefficients in all sub-bands.

Wavelet Energy-based Diagnostic Distortion (WEDD) measure is proposed in [9] to assess the quality of compressed signal in ECG data compression. WEDD was evaluated from the wavelet coefficients of the original and processed ECG signal. The WEDD measure is given as

$$WEDD = \sum_{j=1}^{M+1} w'_j WPRD_j \quad (2.21)$$

where  $w'_j$  is the weight calculated based on energy due to wavelet coefficients in sub-bands defined by

$$w'_j = \frac{\sum_{k=1}^{N_j} w_{(j,k)}^2}{\sum_{j=1}^{M+1} \sum_{k=1}^{N_j} w_{(j,k)}^2} \quad (2.22)$$

The errors in the wavelet coefficients is given as:

$$WPRD = \sqrt{\frac{\sum_{k=1}^{N_j} (w_{j,k} - \tilde{w}_{j,k})^2}{\sum_{k=1}^{N_j} w_{j,k}^2}} \times 100 \quad (2.23)$$

where  $w_{j,k}$  and  $\tilde{w}_{j,k}$  are the wavelet coefficients for original and processed ECG signals and  $N_j$  is the number of sub-band wavelet coefficients at  $j$  level of decomposition.

The multiscale entropy based PRD objective diagnostic distortion measure is proposed in [19]. The PRD between the approximation and detail subband wavelet coefficients of original and processed ECG signals is evaluated and the weights are assigned as the multiscale entropy values of each sub-bands. The MSEPRD measure is given as

$$\begin{aligned} MSEWPRD = w_{AL} \times & \left( \sqrt{\frac{\sum_{k=1}^{N_{AL}} (A_L(k) - \tilde{A}_L(k))^2}{\sum_{k=1}^{N_{AL}} A_L(k)^2}} \times 100 \right) \\ & + \sum_{j=1}^L w_{Dj} \times \left( \sqrt{\frac{\sum_{k=1}^{N_{Dj}} (D_j(k) - \tilde{D}_j(k))^2}{\sum_{k=1}^{N_{Dj}} D_j(k)^2}} \times 100 \right) \end{aligned} \quad (2.24)$$

where  $w_{AL}$  and  $w_{Dj}$  are the weights as multiscale entropy values for Lth approximation and Jth detail wavelet sub-bands. The multiscale entropy values are defined by  $H_j = -\tilde{Y}_j \log(\tilde{Y}_j)$  and  $\tilde{Y}_j = \frac{\bar{E}_j}{\bar{E}_{tot}}$ . The multiscale subband energy at  $j$ th resolution level and total sub-band energy is given as  $\bar{E}_j = \frac{1}{K_j} \sum_{k=1}^{K_j} |C_j(k)|^2$ ,  $C_j(k)$  is the wavelet coefficients,  $j \in (1, 2, \dots, J+1)$  and  $\bar{E}_{tot} = \sum_{j=1}^{J+1} \bar{E}_j$ .

The wavelet energy weighted PRD (WEWPRD) measure is proposed in [20] to evaluate the quality of ECG signal. It is computed as the sum of weighted error energies due to wavelet coefficients of original and processed ECG signals. The weights for the approximation and detail sub-bands are given as

$$w = \left[ \frac{E_{A_j}}{E_t}, \frac{E_{D_j}}{E_t}, \dots, \frac{E_{A_1}}{E_t} \right] \quad (2.25)$$

The wavelet energy PRD is given as

$$WEPRD = \left[ \sqrt{\frac{E_{A_j}^{err}}{E_{A_j}}} \times 100, \sqrt{\frac{E_{D_j}^{err}}{E_{D_j}}} \times 100, \dots, \sqrt{\frac{E_{D_1}^{err}}{E_{D_1}}} \times 100 \right] \quad (2.26)$$

where  $E_{A_j}^{err} = \sum_{k=1}^{N_{A_j}} (A_j(k) - \tilde{A}_j(k))^2$  and  $E_{D_j}^{err} = \sum_{k=1}^{N_{D_j}} (D_j(k) - \tilde{D}_j(k))^2$  are wavelet error energies in approximation and detail sub-bands. The WEWPRD measure is given as

$$WEWPRD = w^T WEPRD \quad (2.27)$$

The wavelet based methods are found to be effective measures in different applications and well correlated with subjective assessment.

### 2.3 ECG Feature Extraction for Disease Detection: A Review

Extracting diagnostic information from normal and pathological ECG signals for detection and classification of cardiovascular diseases have been an active area of research from decades. There are two type of methods used for quantifying diagnostic information from ECG signals. These are direct and indirect methods. The direct method corresponds to the visual inspection of local wave-forms as P-wave, QRS-complex and T-wave amplitudes and duration from ECG. The cardiologist investigate these features for detection and localization of cardiac arrhythmia. On the other hand, the indirect method corresponds to the use of various signal processing and machine learning techniques for detection and localization of cardiovascular diseases. There are number of signal processing techniques like heart rate variability analysis [21–25], discrete and continuous wavelet transform based analysis [26, 27], auto-regressive model coefficients [28], discrete cosine transform coefficients [29], principal component analysis [30, 31], linear discriminant analysis [32], independent component analysis [33], polynomial regression coefficients [34] etc. are reported in literature for extracting clinical diagnostic features from ECG for arrhythmia detection and classification. The detail description of each of these diagnostic information extraction methods are given below.

The heart rate variability features are widely used in applications like cardiovascular disease detection [21], diabetes diagnosis from ECG [22], prognosis of cardiac risk [23], identifying fatigue in elite athletes [24], monitoring sleep apnea from ECG [25] etc. The trace of RR interval with respect to number of beats is termed as heart rate signal. This heart rate signal is subjected to statistical, frequency domain and non-linear analysis for getting the HRV based features. The time domain HRV features are mean of RR-intervals ( $RR_m$ ), standard deviation of RR-interval ( $RR_{std}$ ), mean of heart rates ( $HR_m$ ) and standard deviation of heart rates ( $HR_{std}$ ), RMSSD, SDSD, NN50, PNN50 and HRV triangular index. These features are given as

$$RR_m = \frac{\sum_{i=1}^N RR(i)}{N} \quad (2.28)$$

$$RR_{std} = \sqrt{\frac{\sum_{i=1}^N (RR(i) - RR_m)^2}{N}} \quad (2.29)$$

$$HR_m = \frac{\sum_{i=1}^N HR(i)}{N} \quad (2.30)$$

$$HR_{std} = \sqrt{\frac{\sum_{i=1}^N (HR(i) - HR_m)^2}{N}} \quad (2.31)$$

where  $HR(i) = \frac{60}{RR(i)}$  called as heart rate time series. RMSSD is the square root of mean of square difference between adjacent RR-intervals and given by

$$RMSSD = \sqrt{\frac{\sum_{i=1}^N (RR(i+1) - RR(i))^2}{N}} \quad (2.32)$$

Similarly SDDSD feature is the standard deviation of difference between adjacent RR-intervals and given by

$$SDDSD = \frac{\sum_{i=1}^N (RR_{diff}(i) - \tilde{RR}_{diff})}{N} \quad (2.33)$$

where  $RR_{diff}(i) = (RR(i+1) - RR(i))$  and  $\tilde{RR}_{diff} = \frac{\sum_{i=1}^N (RR(i+1) - RR(i))}{N}$ . The PNN50 feature is evaluated by identifying the RR-interval difference more than 50 ms. The PNN50 is given as

$$PNN50 = \frac{\sum_{i=1}^N ((RR(i+1) - RR(i)) > 50 \text{ ms})}{\sum_{i=1}^N RR_{diff}(i)} \quad (2.34)$$

The frequency domain information of heart rate signals are evaluated using autoregressive model based spectral analysis, discrete Fourier transform (DFT), short time fourier transform and wavelet transform based analysis. The high frequency band (0.15–0.4 Hz) of heart rate signal is related to parasympathetic activity and low frequency band (0.04–0.15 Hz) corresponds to sympathetic activity. The total power in low frequency (LF) band, high frequency (HF) band along with the power spectral density ratio in LF to HF band (LF/HF) are used as frequency domain HRV features. The non-linear HRV features are obtained from the Poincare plot. The  $RR(i+1)$  are plotted as a function of  $RR(i)$ . The non-linear features SD1 and SD2 are obtained from this plot as the standard deviation of the distance of  $RR(i)$  points to the lines  $y = x$  and  $y = -x + 2 \times RR_m$ . Where y and x are termed as  $RR(i+1)$  and  $RR(i)$ .  $RR_m$  is the mean value of heart rate signal. Although HRV analysis is found to be a better information extraction technique from ECG signal for detection of cardiac diseases and other applications, but it has some limitations. HRV analysis doesn't not give any information about local waveform variations like chaotic nature of P-wave in atrial fibrillation, rather it only evaluate the RR-interval variations.

Banerjee and Mitra proposed a cross wavelet based technique for extracting diagnostic information from ECG signals [26]. The wavelet cross spectrum (WCS) and wavelet coherence (WCOH) metrics between template ECG (Normal beat) and abnormal ECG beats are evaluated. Further, these metrics are used to investigate the variations in both QRS-complex and T-wave regions for pathological ECG beats. The cross wavelet coefficients are computed as

$$W^{XY} = W^X W^{Y*} \quad (2.35)$$

where  $W^{XY}$  corresponds to cross wavelet coefficients. The  $W^X$  and  $W^Y$  are wavelet coefficients for  $x(n)$  and  $y(n)$  respectively. The  $x(n)$  and  $y(n)$  are normal and abnormal beats segmented from ECG time series. The WCS is evaluated as the square of cross wavelet coefficients and it is given as

$$WCS(s, t) = |W^{XY}|^2 \quad (2.36)$$

The wavelet coherence (WCOH) of  $x(n)$  and  $y(n)$  are given as

$$WCOH(s, t) = \frac{|W^{XY}|^2}{|W^X|^2 \cdot |W^Y|^2} \quad (2.37)$$

The sum of WCS and WCOH for different morphological features (QT, QRS, ST) are given by

$$\text{sum } WCS(s, t) = \sum_{s=s1}^{s2} \sum_{t=t1}^{t2} WCS(s, t) \quad (2.38)$$

$$\text{sum } WCOH(s, t) = \sum_{s=s1}^{s2} \sum_{t=t1}^{t2} WCOH(s, t) \quad (2.39)$$

The wavelet based feature extraction method for classification of myocardial infarction (MI) was proposed in [27]. The discrete wavelet transform grossly segments the clinical component present in ECG into both approximation and detail coefficients. The energy and entropy due to these wavelet coefficients are evaluated as

$$E_m = \frac{\sum_{j=1}^{N_m} W_{m,n}^2}{N_m} \quad (2.40)$$

$$E_m^a = \frac{\sum_{j=1}^{N_M} S_{M,n}^2}{N_M} \quad (2.41)$$

The  $W_{m,n}$ ,  $m \in (1, 2, \dots, M)$  and  $S_{M,n}$  are detail and approximation wavelet coefficients at level  $M$ . The probability of detail  $p_m$ ,  $m \in (1, 2, \dots, M)$  and approximation  $p_M$  wavelet sub-bands are given as

$$p_m = \frac{E_m^d}{\sum_{m=1}^M E_m^d + E_m^a} \quad (2.42)$$

$$p_M = \frac{E_M^a}{\sum_{m=1}^M E_m^d + E_m^a} \quad (2.43)$$

The entropy is given as

$$H = - \sum_{i=1}^M p_i \log_2 p_i \quad (2.44)$$

The entropy and energy based features are extracted from 2282 normal and 718 myocardial infarction pathology based ECG beats. A threshold based classifier has been used for detection of myocardial Infarction.

The DWT+PCA, DWT+LDA and DWT+ICA based diagnostic feature extraction and beat classification approaches from ECG signals have been proposed in [32, 33]. Initially, the QRS-complex is detected using pan-tomkin's algorithm [35]. After R-point detection, each ECG beats are decomposed into approximation and detail coefficients by using discrete wavelet transform. The PCA, LDA and ICA are used for dimension reduction. The first six components of both approximation and detail coefficients in PCA, ICA and LDA domain are used as diagnostic feature vectors. Further these features are given to both probabilistic neural network and least square support vector machine (LS-SVM) classifier for detection of different cardiac arrhythmia. The combination of discrete cosine transform (DCT) and PCA have been used to extract the diagnostic features from ECG beats [29]. The DCT is applied over ECG beats and the first few coefficients are selected. The co-variance matrix is evaluated for DCT domain signal and then the PCA is used to select first 12 principal components as feature vector. Both probabilistic neural network (PNN) and support vector machine are used for detection and classification of different cardiac arrhythmia. Sun et al. proposed a method for detection of myocardial infarction based on ST-segment analysis [34]. First, the R, S and T points are detected based on derivative based algorithm. Then, the 200 samples from each ST-segment along each lead heart beats of MEKG are segmented. A fifth order polynomial curve fitting is used over those 200 samples along each beats and the six polynomial coefficients are used as feature vectors. A total of 72 dimensional polynomial coefficient along each lead of MEKG, RR-intervals and ST-segment width to height ratio as features and multi instance learning as classifier is used for MI detection. The principal component analysis and kernel principal component analysis based analysis of ECG

signal for detection of respiratory disorder were proposed in [30, 31]. The principal components are selected based on statistical test and these values are used as diagnostic features for detection of respiratory disorder and other cardiac arrhythmia. Dingfei et al. used the Auto-regressive (AR) model coefficients as diagnostic features to classify normal sinus rhythm (NSR) and various cardiac arrhythmia [28]. AR model coefficients are evaluated from five abnormal ECG beats such as ventricular tachycardia (VT) ventricular fibrillation (VF), atrial premature contraction (APC), premature ventricular contraction (PVC), supraventricular tachycardia (SVT) and normal ECG beat. The decision tree based classifier has been to classify both normal and arrhythmia beats from the AR model coefficient based diagnostic feature vector.

The sample entropy quantifies the randomness in a signal [36]. If the signal is regular (not changing) then the sample entropy value is low. Similarly, if the signal is continuously changing and having irregularity then the sample entropy is more. Recently, number of approaches based on sample entropy are reported in literature for cardiac arrhythmia detection [37, 38] and EEG based seizure detection and classification [39]. The evaluation of sample entropy for a time series data is given below. Let's consider a N-point time series ECG data  $x(n) = [x(1), x(2), \dots, x(N)]$ . The two parameters used to derive the sample entropy are coefficients of tolerance ( $r$ ) and dimension of template vector ' $m$ '. The  $k$ th template vector for ECG time series is given as  $x_m = [x(k), x(k+1), \dots, x(k+1-m)]$ . Each of the  $k$ th template vector is having dimension ' $m$ '. The distance between ' $i$ ' and ' $j$ 'th template vector is given as

$$d[x_m(i), x_m(j)] = \max[|x(i+k) - x(j+k)|] \quad (2.45)$$

where  $k \in [0, m-1]$ ,  $i \neq j$  and  $i, j \in 1, 2, \dots, N-m$ . The number of distances are counted for which the value of  $d \leq R$ , where  $R = r \times sd$  and ' $sd$ ' is the standard deviation of ECG time series. The ' $i$ 'th total number of distance is denoted as  $B_i^m(r)$ . The  $B^m(r)$  is evaluated as

$$B^m(r) = \frac{\sum_{i=1}^{N-m} B_i^m(r)}{(N-m-1)(N-m)} \quad (2.46)$$

The  $B^{m+1}(r)$  is evaluated in similar way by replacing the dimension template vector to  $m+1$ . The sample entropy is evaluated as the negative logarithmic ratio of  $B^{m+1}(r)$  and  $B^m(r)$  and given by

$$sampEN(m, r, N) = -\ln \left[ \frac{B^{m+1}(r)}{B^m(r)} \right] \quad (2.47)$$



## 2.4 MSD Diagnostic Measure for MECCG

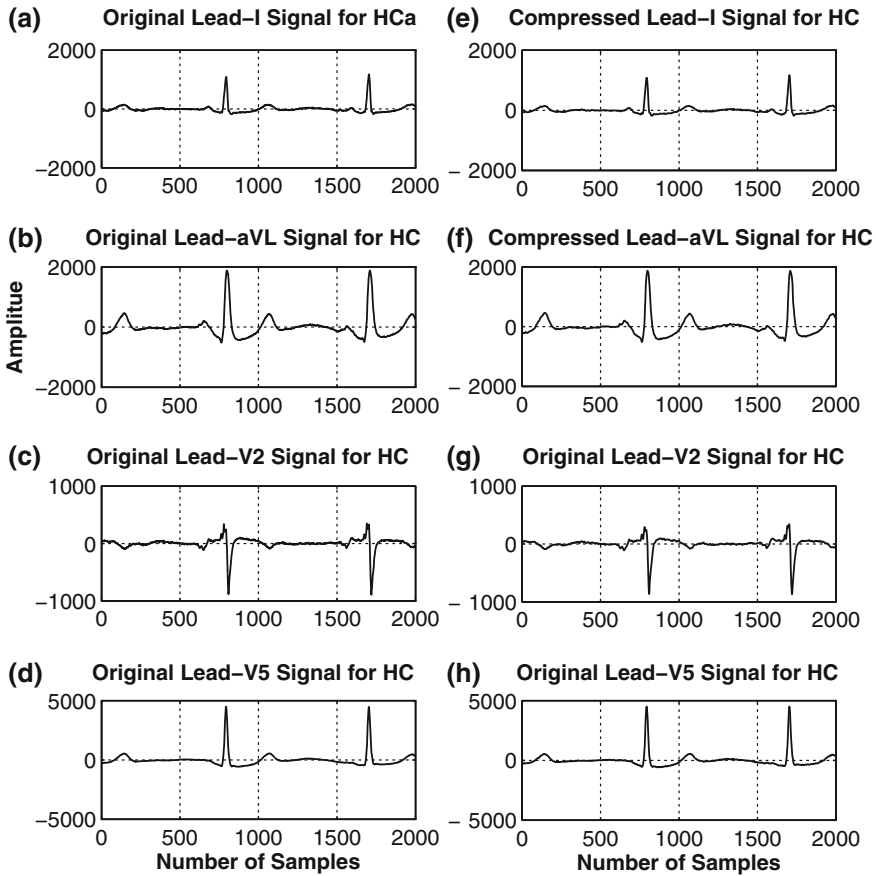
The state-of-art objective diagnostic and non-diagnostic measures such as PRD, MSE, MAE, WDD, WEDD, WWPRD, MSEWPRD, WEWPRD etc. are limited to single channel ECG signals. There are numbers of MECCG data processing techniques such as multiscale PCA (MSPCA) [40], multivariate empirical mode decomposition [41], compressive sensing based MECCG compression [42], DCT and karhunen loeve transform (KLT) based MECCG compression [43] etc. are reported from literature. For these MECCG processing schemes, the aforementioned objective diagnostic and non-diagnostic measures are computed individually along each channel. Multivariate sample entropy (MSampEn) is the natural extension of sample entropy for multichannel signals [44]. This measure quantifies the confusionness or irregularity of signal along each channel. ECG signal with atrial fibrillation pathology has higher value of sample entropy than that normal sinus rythem [45]. In this work the MSampEn(e) is evaluated for original and compressed MECCG signal and the diagnostic measure is defined as

$$MSD = e_o - e_r \quad (2.48)$$

where  $e_o$  and  $e_r$  are the multivariate sample entropy values for original and processed MECCG signals.

## 2.5 Results and Discussions

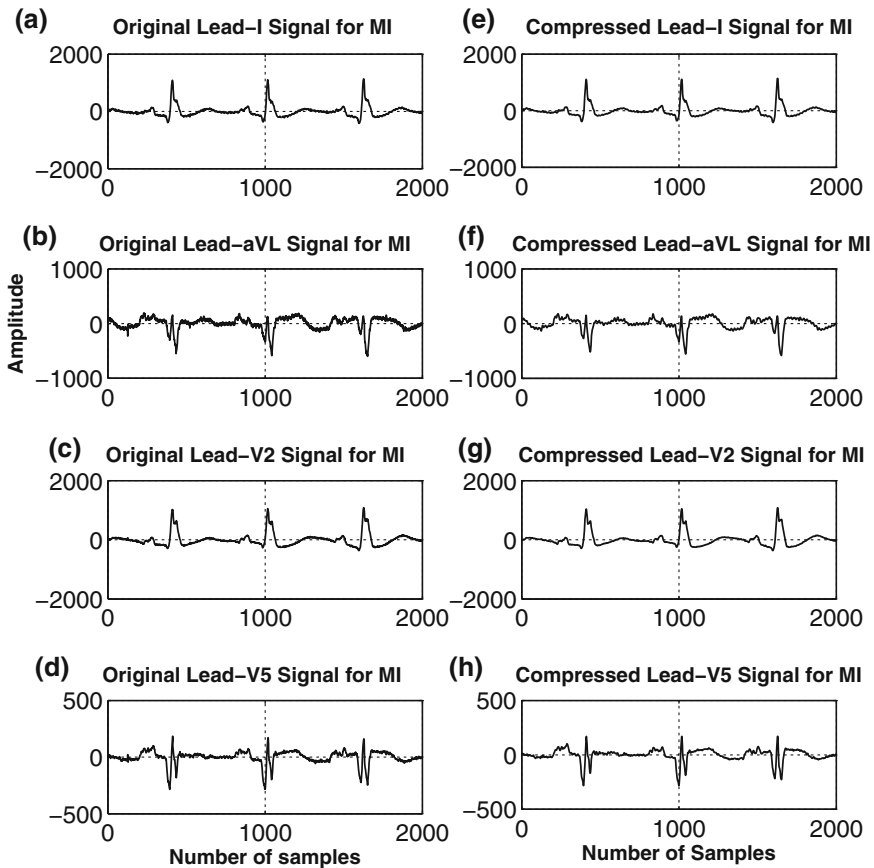
For evaluation of the proposed diagnostic measure, the combination of PCA and discrete cosine transform based MECCG compression framework is used. The DCT based MECCG compression was proposed in [43]. In this work, first the PCA is applied to MECCG signal and according to diagnostic importance the first six principal components (PCs) are retained [40] and others PCs are discarded. The DCT is applied to the PCA domain multivariate signal and due to energy compaction property the first few samples are retained. The transformed multivariate signal is uniformly quantized and huffman encoded for compression. Both 8-bit and 10-bit quantizer are used in this work. The compressed (reconstructed) signal is obtained by huffman decoding, inverse quantization followed by inverse DCT and PCA based reconstruction. The MECCG signals are taken from PTB diagnostic [46] database. In this database, each of the MECCG signals has sampled frequency and number of bits of 1000Hz and 16 respectively. Figures 2.2 and 2.3 shows the compressed signals along-with the original signals for four channels (lead-I, lead-aVL, lead-V2 and lead-V5) for healthy control (HC) and myocardial infarction (MI) pathology based MECCG. It is observed that the compressed signals are denoised and the clinical components are preserved in both the cases (HC and MI). The PRD, WEDD and RMSE distortion measures are evaluated along each lead and the average of these values are defined as



**Fig. 2.2** Original signals (a), (b), (c) and (d) and Compressed signals (e), (f), (g) and (h) for Lead-I, aVL, V2 and V5 for HC based MCECG respectively

multichannel PRD (MPRD), multichannel WEDD (MWEDD) and multichannel RMSE (MRMSE).

The proposed MSD measure is also evaluated and compared with the MPRD, MWEDD and MRMSE measures. As the proposed measure is based on multivariate sample entropy, the irregularity in clinical components present in processed MCECG signal results a negative value of MSD. The MSD,  $e_o$ ,  $e_r$ , MPRD, MWEDD and MRMSE values for HC and MI pathology based MCECG signals for different compression ratios (CRs) are shown in Table 2.1. Results are shown for 10 multichannel ECG signals with different compression ratios, which include normal and pathological cases. In HC1 dataset Compression ratio (CR) value of 13.16:1 produces MPRD, MWEDD and MRMSE values of 4.36 %, 1.98 % and 8.51 for processed MCECG signal. It is observed that for high values of CR, the corresponding MPRD and MWEDD, MRMSE values are also high. This signifies the higher distortion in clinical infor-



**Fig. 2.3** Original signals (a), (b), (c) and (d) and Compressed signals (e), (f), (g) and (h) for Lead-I, aVL, V2 and V5 for MI pathology based MEEG respectively

mation for the processed MEEG signals with higher CR values. For HC1 dataset the multivariate sample entropy values for original and processed MEEG signals are found to be 0.69 and 0.68. The MSD value is very small (0.01). This signifies that the processed MEEG signal is regular (not changing) and the clinical components are also preserved. Similarly, for HC3 dataset with 8 bit quantization level, the CR is found to be 15.70:1. This CR value produces MPRD, MWEDD and MRMSE values of 4.08 %, 2.85 % and 14.64. The multivariate sample entropy values for original and processed MEEG signals are found to be 1.01 and 1.03. The MSD measure shows a negative value of  $-0.02$ , this signifies there may be the slight change in the regularity of clinical components ('PQRST' morphologies) present in processed MEEG signals. For MI2 dataset with 8-bit quantizer the CR value of 14.44:1 produces a MPRD, MWEDD and MRMSE values of 6.37 %, 3.41 % and 15.00. The multivariate sample entropy for original and processed MEEG signals are found to be 1.82 and 1.85.

**Table 2.1** Performance of MSD, MWEDD, MPRD and MRMSE over MECG data compression

Record	Q. Bit	CR	MPRD (%)	MWEDD (%)	MRMSE	$e_o$	$e_r$	MSD
HC1	8	13.16	4.36	1.98	8.51	0.69	0.68	0.01
HC2	8	15.11	4.75	2.73	9.72	1.70	1.71	-0.01
HC3	8	15.70	4.08	2.85	14.64	1.01	1.03	-0.02
HC4	8	14.80	4.36	2.71	11.51	1.35	1.34	0.01
HC5	8	14.73	5.27	2.85	13.26	1.01	0.94	0.06
HC1	10	10.66	3.62	1.04	6.66	0.69	0.66	0.02
HC2	10	12.03	2.78	0.95	5.42	1.70	1.69	0.01
HC3	10	12.73	1.72	0.78	5.58	1.01	1.02	-0.01
HC4	10	11.78	3.12	0.83	7.65	1.35	1.34	0.01
HC5	10	11.58	4.01	1.09	8.69	1.01	0.96	0.04
MI1	8	13.44	6.78	3.57	11.41	1.51	1.53	-0.02
MI2	8	14.44	6.37	3.41	15.00	1.82	1.85	-0.02
MI3	8	14.70	6.18	2.59	13.80	1.53	1.49	0.04
MI4	8	13.01	9.76	3.99	13.98	1.31	1.34	-0.02
MI5	8	14.71	5.62	3.25	16.62	2.03	2.01	0.02
MI1	10	10.81	5.76	2.06	8.95	1.51	1.48	0.02
MI2	10	11.52	5.26	2.07	11.24	1.82	1.85	-0.03
MI3	10	11.62	5.35	1.50	10.92	1.53	1.49	0.04
MI4	10	10.55	9.11	2.95	12.23	1.31	1.28	0.03
MI5	10	11.58	4.38	1.71	12.15	2.03	2.04	-0.01

From this observation it is clear that the low MPRD, MWEDD and MRMSE does not guarantee the processed MECG signals to be clinically significant. The deviation of multivariate sample entropy from original value in MI2 dataset, shows that there is a small variation in the clinical components present in the processed MECG signal. This change is correctly quantified with the help of proposed MSD based diagnostic measure. The results for all other MECG dataset shows that the MSD measure is effective to quantify the regularity in the clinical component present in original and processed MECG signals.

## 2.6 Conclusion

In this paper, a review on state-of-art diagnostic information extraction approaches and their applications in various ECG signal processing such as filtering, compression and disease detection are presented. Then, a new diagnostic measure is proposed for evaluating the quality of multi lead ECG (MECG) signals. This measure (MSD) is

defined as the difference between multivariate sample entropy values for original and processed MEGC signals. The effectiveness of proposed MSD measure alongwith MPRD, MWEDD, MRMSE are tested over MEGC data compression framework. Comparison shows that the proposed measure is effective in quantifying clinical information in normal and pathological MEGC signals.

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