Intelligent electrocardiogram pattern classification and recognition using low-cost cardio-care system

Rajendra G. Sutar1,2, Ashwin G. Kothari2

1Electronics Department, Sardar Patel Institute of Technology (S.P.I.T.), Mumbai University, Mumbai, India
2Electronics and Communication Department, Visvesvaraya National Institute of Technology (V.N.I.T.), Nagpur, India
E-mail: rajendrasutar73@gmail.com

Abstract: Electrocardiogram (ECG) contains detailed information regarding incidental abnormality of a subject. Manual analysis of a long time ECG record is a lengthy process. Computerised ECG analysis supports clinicians in decision making. While designing a low-cost diagnostic support system, constraints on the system resources limit the processing speed, eventually affecting the reliability. To resolve these issues, three key factors have been addressed in this study: the feature extraction method, total number of features and the database used. For feature extraction, ‘polar Teager energy’ algorithm has been developed, yielding nearly 70% saving in processing time as compared to other well-known methods. Using features with linear relationship leads to reduction in feature vector dimension, without compromising its classification performance. Therefore the linear relationship between two ECG features, namely ‘informational entropy’(S) and ‘mean Teager energy’ has been revealed. These features are utilised for ECG beat classification using ‘fuzzy C-means clustering’ algorithm. The algorithm is evaluated using the MIT-BIH database and then tested by ECG measured with the cardio-care unit. The QRS detection performance of the proposed method is very good, with 0.27% detection error rate. For classification of ECG beats, average sensitivity and positive prediction rate achieved are 98.93% each.

1 Introduction

Cardiovascular disease (CVD) is the major cause of mortality in the world. According to a survey of World Health Organization (WHO), over 80% of CVD deaths take place in low and middle-income countries [1]. In remote places of such countries, the rate of mortality is high because of the poor medical facilities and inadequate number of medical experts. Under such circumstances, for sustainable clinical practices and to provide low-cost medical services, intelligent medical diagnostic decision support system plays an important role. Such a system has to be cost effective and yet reliable. This will aid clinicians in decision making. The design of such a system should use optimum resources. For high reliability, two factors are of prime importance: accuracy and processing time. They are largely dependent on the method used for feature extraction, number of features required, classifier performance and the database used to train the system. There are several well-known classifiers developed by the researchers in the past. But many of them perform badly while processing an unknown database, which makes the system unreliable. Although some of them perform well, they are highly complex, utilising more computational resources and ultimately increasing the cost. Some of them, being non-synthesisable, may not be implemented in hardware for the customised application. ‘Feature extractor’ is also a factor that governs the system reliability. Computationally complex method of feature extraction delays the diagnostic decision, thereby reducing its reliability. Among the diverse electrocardiogram (ECG) features, use of features with linear relationship not only improves the classification accuracy but also reduces their number, and in turn saves the time required for feature extraction. Hence, to design a low-cost diagnostic decision support system, the issues of cost and reliability must be resolved.

In the last few decades, there has been a widespread use of computational intelligence for ECG analysis for achieving low cost and high reliability. Several techniques have been devised for classification of ECG beat patterns. The studies presented in [2–4], use support vector machines (SVMs) and wavelet transform. Weighted conditional random fields [5] is another technique used recently, which addressed the class unbalance in the context of the database used to train the algorithm. In [6], ECG beats have been classified using morphological and dynamic features extracted by wavelet transform, and achieved 99.71% classification accuracy. In [7], ‘linear discriminant’ (LD)-based model has been reported, which used diverse ECG features to limit the false positive rate to 1.2%. It utilised the standards recommended for reporting performance results of cardiac rhythm algorithms, by the Association for the Advancement of Medical Instrumentation (AAMI). Conforto et al. [8] achieved 99.8% sensitivity using neural network and SVM for classification and Pan–Tompkin’s algorithm for beat detection. It is among a few studies that have adopted AAMI standards. Faezipour et al. [9] presented ‘Patient
Adaptive Profiling Scheme’ and achieved 97.42% classification accuracy. It used wavelet transform for feature extraction. In [10] Ince, Kiranyaz and Gabbouj presented a generic method, employing combination of the wavelet transform as a feature extractor and the artificial neural network as a classifier. A method employing integrate and fire pulse based feature extraction, and LD-analysis-based classification, has been presented in [11]. The studies presented in [12–16] used fuzzy clustering, neural network classifiers, and most of them used the wavelet-based feature extractor. In [17] fuzzy C-means clustering (FCM)-based classification algorithm has been presented. It uses the ‘difference operation method’ (DOM) for beat detection. SVM and particle swarm optimisation [18], and a mixture of expert’s network [19, 20] are some of the other studies employing computational intelligence for ECG analysis. A review of neural-network-based ECG pattern classification methods has been presented in [21].

In the literature, it has been observed that the objective of several studies is to achieve higher accuracy, in lieu of increased complexity and the cost. The issues of cost and reliability, towards the design of diagnostic decision support system, are yet to be resolved. The objective of the work presented in this paper is to resolve these issues. In this method, the algorithm based on polar Teager energy (PTE) of ECG has been used for QRS detection, which reduces the processing time as compared to other well-known methods. QRS detection is followed by beat segmentation, based on R–R interval. Further, the linear relationship between two features, ‘informational entropy’ and ‘mean Teager energy’ (MTE) has been revealed. Each segmented beat has been classified based on these two features, using the FCM clustering technique. The algorithm has been evaluated using the MIT-BIH arrhythmia database [22]. To verify the performance of the algorithm while processing unknown ECG data, the low-cost cardio-care unit has been designed. Fig. 1 illustrates the schematic block diagram of the proposed system. It has been trained using the MIT-BIH database, to classify the ECG beat into five classes – normal (NORM), premature ventricular contraction (PVC), PACED, left bundle branch block (LBBB) and right bundle branch block (RBBB). The system computes the cluster centres for these classes. When an unknown ECG beat is applied, it classifies the beat into one of the five classes based on minimum distance with respect to the cluster centres.

2 Materials and methods

2.1 ECG database

The proposed method has been evaluated in two different stages: beat detection and beat classification. For beat detection three different resources have been used. It include middb-45 records, ahdab (American Heart Association database)-2 records and edb (European St-T database)-2 records. The classification performance has been evaluated using the MIT-BIH database. We used ECG beats from five different categories: for NORM, tapes-103, 113, 115, 117, 121 and 123; for LBBB, tapes-109, 111, 207 and 214; for RBBB, tapes-118, 124, 212 and 231; for PVC, tapes-200, 208 and 233; for paced beat, tapes-107, 217. A total of 19 records of approximately 30 min length were used to evaluate the algorithm. To investigate the system performance while processing the unknown database, we used a database generated by the low-cost cardio-care unit.

2.2 Cardio-care unit

It consists of a three lead ECG amplifier, along with microchip’s peripheral interface controller (PIC) microcontroller 16F877 for digitisation and serial transmission of the data to the computer via RS232. As the desired system should be cost effective and fast, to limit the hardware and processing time only three leads I, II and III are considered. Cardio-care unit consists of three stages: signal conditioning, analogue-to-digital converter (ADC) and RS-232 for serial data transmission.

2.2.1 Signal conditioning: Fig. 2 shows the analogue section of the cardio-care unit, used for signal conditioning. It consists of driven right leg (DRL) circuit with little modification as in [23]. To reduce the effect of common mode signals, three resistors (10 MΩ each) are connected at the output of buffers. Right leg buffer has 2.7 KΩ resistor in series with its output, so as to limit current from external sources and also at the input of each buffer to balance the DRL circuit. It follows lead select switch, which is a two pole-three way rotary switch used to select a lead from the three leads. The difference signal selected by the switch is applied to the input of the instrumentation amplifier. The total voltage gain required is 1000, which has been achieved through two amplifier stages so as to avoid saturation. For the design of the instrumentation amplifier and filter stages, operational amplifier TL082 has been used. It has a good CMRR, typically 100 dB. To improve the signal quality, two analogue filters namely band-pass (0.5–100 Hz) and twin-T notch (50 Hz) are used [24]. The first-order Butterworth sections for band pass and notch filters have been designed with these cut-offs using the relation, \( f = 1/2πRC \). For high-pass section with 0.5 Hz cut-off, approximate values of capacitor and resistor chosen are 0.22 μF and 1.5 MΩ, respectively. For low-pass section with 100 Hz cut-off, approximate values of capacitor and resistor used are 0.1 μF and 47 KΩ, respectively. 50 Hz noise is a dominant factor in achieving the signal quality, and hence accurate component values must be chosen for its implementation. With 0.1 μF (2C = 0.2 μF) capacitor and...
31.8 KΩ resistance ($R/2 = 15.9$ KΩ), twin-T notch filter has been implemented. In [24] Peter et al. have used higher order sections to achieve these filters. To achieve the signal quality using only analogue filters requires increased hardware, whereas achieving it with only digital filters results in increased computational burden. Therefore, to optimise it, we used first-order analogue sections and further digital filters in the feature extraction algorithm.

2.2.2 ADC and serial data transmission: Microchip’s PIC 16F877 has been used for digitisation and serial transmission of the signal. For digitisation, the internal ADC of the microcontroller has been used. It has 10 bit (eight channels) ADC which is very sensitive to the over-voltage, hence is protected by a pair of external diodes. The microcontroller works with external 20 MHz crystal oscillator for clock generation. CRT display refreshing rate must be 50 (for 50 Hz supply) to avoid flicker. It has been intended to display 2 s (refreshing time) of the ECG on CRT screen which is 256 bytes wide, the sampling rate of 128 samples per second (256/2) has been selected. PIC’s internal ADC has peak-peak voltage of 4 V. The 1/2 LSB error is the maximum error allowed for the A/D to meet its specified resolution. The minimum acquisition time (19.72 μs) calculated assuming 1/2 LSB error, requires 1024 steps (i.e. 10 bit resolution). Hence, to transmit the digitised signal via RS-232, 10 bit digital data has been converted to higher and lower byte using 8 bit frame arrangement wherein each byte consists of 5 bit digital data of a sample. Remaining 3 bits contains information regarding the data bits, whether they are upper or lower bits. For selecting the baud rate, DIP switch has been used. Default baud rate is 9600 bps. For serial transmission of the data to the host computer, its voltage level must be changed, because RS232 needs +3 to +12 V for logic ‘0’ and −3 to −12 V for logic ‘1’. It is achieved using IC MAX232. The manufacturing cost of the ‘cardio-care unit’ is approximately 500 Indian Rupees. Fig. 3 shows the digital section of the cardio-care unit.

2.3 QRS detection

QRS detection is an important step towards ECG feature extraction, because it is a reference point for extraction of several other features. The fast and accurate detection of QRS offers time efficiency and reliability in the ECG signal analysis. We used two stages for QRS detection: pre-processing and QRS decision.

2.3.1 Pre-processing: In order to improve the signal quality, we used digital filters as in [25]. The reason we used digital filters in spite of using analogue filters is that we used first-order analogue filters in hardware so as to limit the hardware requirement, making it cost effective. Thus, the signal quality has been improved using analogue as well as digital filtering techniques. Noise because of various sources such as electrode contact noise, motion artefacts, muscle contraction, electromagnetic interference and power line interference has been eliminated in this stage.

2.3.2 QRS decision: The flow diagram of the PTE algorithm is shown in Fig. 4. For QRS decision we have introduced the PTE algorithm which is computationally efficient. Pre-processed signal passes through low pass filter with cut-off frequency 2 Hz, in order to ensure the QRS complex. It follows computation of PTE that is being described as follows:

![Analogue section of the cardio-care unit](image-url)
Discrete time signal $x[n]$ of a continuous time signal $x(t)$ sampled with sampling frequency $f_s$ is given as

$$x[n] = A \cos\{\Omega n + \phi\}$$  \hspace{1cm} (1)

where $\Omega$ is the digital frequency in radians/sample and $\phi$ is the arbitrary initial phase in radians.

Two adjacent points of this signal are given as

$$x[n + 1] = A \cos\{\Omega[n + 1] + \phi\}$$  \hspace{1cm} (2)

$$x[n - 1] = A \cos\{\Omega[n - 1] + \phi\}$$  \hspace{1cm} (3)

Using (1)–(3) it has been proved that the non-linear energy

---

**Fig. 3**  *Digital section of the cardio-care unit*

**Fig. 4**  *Flow diagram of the PTE algorithm*
there can be four possible conditions given as

\[ \Delta = \{ x[n+1] \} \{ x[n-1] \} \]

Let \( \Delta = \{ x[n+1] \} \{ x[n-1] \} \). Then from (4) it is obvious that there can be four possible conditions given as

(a) \( \Delta > \{ x[n] \}^2 \), \( x[n] > 0 \)
(b) \( \Delta < \{ x[n] \}^2 \), \( x[n] > 0 \)
(c) \( \Delta > \{ x[n] \}^2 \), \( x[n] < 0 \)
(d) \( \Delta < \{ x[n] \}^2 \), \( x[n] < 0 \)

where (a) and (b) correspond to positive signal which includes R peak whereas (c) and (d) correspond to negative signal which includes S wave. But, as per the morphology of R and S waves, condition (a) is never true for R peak (causing \( E[n] < 0 \)), and condition (d) is never true for S point (causing \( E[n] > 0 \)). Hence to represent R and S points, \( E[n] \) can be polarised using conditions (b) and (c) as

\[ E'[n] = \begin{cases} -E[n], & x(n) < 0 \\ +E[n], & x(n) \geq 0 \end{cases} \]

where \( E'[n] \) is referred to as PTE. Fig. 5 illustrates how PTE is useful to differentiate R and S waves and how un-polarised TE may cause false positive of R peak.

The decision rule applied for finding R peak zone is as follows

If \( E'[n] \geq E_{th} \rightarrow \) R-peak zone
If \( E'[n] < E_{th} \rightarrow \) none

where \( E_{th} \) is known as adaptive threshold which is updated by

\[ E_{th} = \sigma \delta \ast \text{PEAK} + (1 - \sigma)E_{th} \]

where \( \sigma \) is termed as ‘forgetting coefficient’. Each new value of the threshold is determined from the running estimate of the PTE peak as well as the preceding and current values of the threshold itself and a weighting factor \( \delta \) is used for determining the contribution of peak values to threshold adjustment [27]. R peak index is then searched within a window of R-peak zone for the maximum value. This index has been referred to as location of R peak on the X-axis, i.e. \( R_{pe} \). As R peak index is obtained, amplitude of R peak is obtained by mapping the R peak index in the pre-processed signal. The corresponding value has been referred to as \( R_{pe} \). Hence R peak has been detected. Further, R-R interval is computed using equation

\[ RR(i) = R_{pe}(i+1) - R_{pe}(i) \]

where \( R_{pe}(i) \) denotes the index of \( i \)th R peak and \( R_{pe}(i+1) \) denotes the index of \((i+1)\)th R peak. The length of R-R interval is useful in deciding the length of search window applied for detection of Q and S points. The search window ranging from 5 to 35 samples prior to R peak has been considered for detecting Q wave. The search window ranging from 3 to 75 samples corresponding to 0.27 s post R peak has been used to search S point.

2.4 ECG segmentation

False positive of an R peak causes considerable irregular R-R interval. Minimum and maximum values of R-R interval are essential to ensure the true R peak. For the same, several methods have been reported by researchers. We have used the Pan and Tompkins [25] method, that is, minimum R-R interval to be 360 ms. Segmentation of the pre-processed ECG signal has been done using R-R intervals. Let \( X_{pe}(j) \) be the segment of \( j \)th ECG beat for which segment begins at \( (R_{pe}(j) - [RR(j-1)])/2 \) and ends at \( (R_{pe}(j) + [RR(j)])/2 \).

2.5 Beat feature extraction

For classification of ECG beat, we used only two features: ‘MTE’ and ‘informational entropy’. The term entropy signifies the state of a system in the field of statistical mechanics. It has been interpreted as a measure of potential energy in the field of classical thermodynamics. Use of entropy for measurement of the randomness of probabilistic

\[ E_{th} = \{ x[n] \}^2 \]

where \( \Delta \) includes peak whereas (c) and (d) correspond to negative signal which includes S wave. But, as per the morphology of R and S waves, condition (a) is never true for R peak (causing \( E[n] < 0 \)), and condition (d) is never true for S point (causing \( E[n] > 0 \)). Hence to represent R and S points, \( E[n] \) can be polarised using conditions (b) and (c) as

\[ E'[n] = \begin{cases} -E[n], & x(n) < 0 \\ +E[n], & x(n) \geq 0 \end{cases} \]

where \( E'[n] \) is referred to as PTE. Fig. 5 illustrates how PTE is useful to differentiate R and S waves and how un-polarised TE may cause false positive of R peak.

The decision rule applied for finding R peak zone is as follows

If \( E'[n] \geq E_{th} \rightarrow \) R-peak zone
If \( E'[n] < E_{th} \rightarrow \) none

where \( E_{th} \) is known as adaptive threshold which is updated by

\[ E_{th} = \sigma \delta \ast \text{PEAK} + (1 - \sigma)E_{th} \]

where \( \sigma \) is termed as ‘forgetting coefficient’. Each new value of the threshold is determined from the running estimate of the PTE peak as well as the preceding and current values of the threshold itself and a weighting factor \( \delta \) is used for determining the contribution of peak values to threshold adjustment [27]. R peak index is then searched within a window of R-peak zone for the maximum value. This index has been referred to as location of R peak on the X-axis, i.e. \( R_{pe} \). As R peak index is obtained, amplitude of R peak is obtained by mapping the R peak index in the pre-processed signal. The corresponding value has been referred to as \( R_{pe} \). Hence R peak has been detected. Further, R-R interval is computed using equation

\[ RR(i) = R_{pe}(i+1) - R_{pe}(i) \]

where \( R_{pe}(i) \) denotes the index of \( i \)th R peak and \( R_{pe}(i+1) \) denotes the index of \((i+1)\)th R peak. The length of R-R interval is useful in deciding the length of search window applied for detection of Q and S points. The search window ranging from 5 to 35 samples prior to R peak has been considered for detecting Q wave. The search window ranging from 3 to 75 samples corresponding to 0.27 s post R peak has been used to search S point.

2.4 ECG segmentation

False positive of an R peak causes considerable irregular R-R interval. Minimum and maximum values of R-R interval are essential to ensure the true R peak. For the same, several methods have been reported by researchers. We have used the Pan and Tompkins [25] method, that is, minimum R-R interval to be 360 ms. Segmentation of the pre-processed ECG signal has been done using R-R intervals. Let \( X_{pe}(j) \) be the segment of \( j \)th ECG beat for which segment begins at \( (R_{pe}(j) - [RR(j-1)])/2 \) and ends at \( (R_{pe}(j) + [RR(j)])/2 \).

2.5 Beat feature extraction

For classification of ECG beat, we used only two features: ‘MTE’ and ‘informational entropy’. The term entropy signifies the state of a system in the field of statistical mechanics. It has been interpreted as a measure of potential energy in the field of classical thermodynamics. Use of entropy for measurement of the randomness of probabilistic
events was revealed by Shannon [28]. The connection between entropy of river basin network (in the context of basin elevation) and potential energy of a river network has been explored by [29] in the field of hydrology. We have extended this concept to reveal the novel relation between ‘informational entropy’ and ‘MTE’ of the ECG signal.

ECG is highly non-stationary and non-linear signal. Variation in its non-linear constituent differentiates ECG patterns from normal to arrhythmia situation. The non-linear constituent can be measured in terms of Teager energy (TE) patterns from normal to arrhythmia situation. The non-linear constituent can be measured in terms of Teager energy (TE) patterns from normal to arrhythmia situation. Let us consider an ECG beat values from the mean for a particular pattern causes deviation of these sample values from the mean for a particular pattern causes variation in its entropy value. Let us consider an ECG beat having its TE as $E_i$, the informational entropy $S$ of the ECG beat can be expressed as

$$S = - \sum_{i=1}^{n} p_i \ln p_i$$

(10)

By maximising $S$ and applying the principle of maximum entropy [30], we can determine the probability distribution, $P = (p_1, p_2, p_3, \ldots, p_n)$, subject to the given information on sample TE. Let us assume that the only information available on the ECG beat is the MTE of the samples given by

$$E_i = \sum_{i=1}^{n} p_i E_i$$

(11)

and $p_i$ values as

$$\sum_{i=1}^{n} p_i = 1$$

(12)

Applying the principle of maximum entropy

$$p_i = e^{-AE_i} / \sum_{i=1}^{n} e^{-AE_i}$$

(13)

where $\lambda$ is Lagrange multiplier and $n$ is the number of samples over QRS interval.

Rearranging (13) in logarithmic form and solving for $E_i$

$$E_i = (-1/\lambda) \log p_i + (-1/\lambda) \log \sum_{i=1}^{n} e^{-AE_i}$$

(14)

Letting $(1/\lambda) = \alpha$ and $\sum_{i=1}^{n} e^{-AE_i} = \beta$ in (14)

$$E_i = -\alpha \log p_i \beta$$

(15)

Using (15) in (11) we obtain

$$E_i = -\alpha \sum_{i=1}^{n} p_i (\log p_i) \beta$$

(16)

Hence, using (1) MTE is given as

$$E_i = \alpha S - \alpha \log \beta$$

(17)

In [29], Fiorentino et al. defined $\alpha$ as DT, where $T$ represents temperature. As temperature in signal has no relevance, by analogy (as MTE has been calculated over QRS interval), $\alpha = n$. Finally, (17) shows the relation between MTE of an ECG beat and its entropy $S$. The number of samples over QRS duration is taken as constant, equal to maximum QRS interval with reference to R peak. Taking $\alpha$ and $\beta$ as constant values, a linear relation between ‘$S$’ and ‘MTE’ of an ECG beat can be shown.

2.6 Heartbeat classification

We selected five types of records for this study from the MIT-BIH database. From these records, ECG beats of five different classes namely, NORM, PVC, PACED, LBBB and RBBB are used. For the proposed system, a superior classification algorithm was required in order to make it reliable. To suit our application, we used the FCM clustering algorithm presented in [31] to compute cluster centre for each class. It has been described as follows:

Let $X^{'} = \{x_1; x_2; \ldots; x_N\}$ be a set of given feature vectors for $N$ ECG Beats and $V = \{v_1; v_2; \ldots; v_C\}$ be a set of cluster centres. FCM is used to partition $N$ data points into $C$ clusters by minimising objective function given in (18)

$$J(X; U, V) = \sum_{i=1}^{N} \sum_{j=1}^{C} (u_{ij})^m \|x_j - v_i\|^2, \quad 1 < m < \infty$$

(18)

where $m$ is the weighting exponent which determines the fuzziness of the clusters, $\|\|$ is the Euclidean norm and $U = (u_{ij})_{N \times C}$ is a fuzzy partition matrix which satisfies the following conditions

$$u_{ij} \in [0, 1], \quad 1 \leq i \leq C, \quad 1 \leq j \leq N$$

(19)

$$\sum_{i=1}^{C} u_{ij} = 1, \quad 1 \leq j \leq N$$

(20)

Each element $u_{ij}$ indicates the membership degree to which data point $X_j$ belongs to $i$th cluster. Minimisation of the objective function is an iterative optimisation algorithm which can be summarised as the following steps:

1. From the given feature vector set $X$, let each feature vector $X_j$ has two features, ‘MTE’ and ‘$S$’ given as

$$X_j = \begin{bmatrix} x_{j1} \\ x_{j2} \end{bmatrix} = \begin{bmatrix} \text{MTE} \\ S \end{bmatrix}, \quad j = 1, 2, \ldots, N$$

(21)

2. Select the number of clusters $C$, the weighting exponent $m$, and the termination threshold $\epsilon$.

3. Set the counter $t$ to 0 and initialise the membership matrix $U^{(0)}$ with random values between 0 and 1 such that the constraints in (19) and (20) are satisfied.

4. $t ← t + 1$.

5. Compute the cluster centres by the following equation

$$u_{ij}^{(t)} = \frac{1}{\sum_{j=1}^{N} (u_{ij}^{(t-1)})^m x_j}{\sum_{j=1}^{N} (u_{ij}^{(t-1)})^m}, \quad 1 \leq i \leq C$$

(22)
6. Update the membership matrix by the following equation

\[ u_{ij}^{(t)} = \frac{1}{\sum_{k=1}^{C} (\| x_j - v_{i}^{(t)} \| / \| x_j - v_{k}^{(t)} \|)^{(2/m-1)}}, \]

\[ 1 \leq i \leq C, \quad 1 \leq j \leq N \tag{23} \]

7. If \( \| U^{(t)} - U^{(t-1)} \| < \varepsilon \) then stop otherwise go to step 4.

8. If the final \( u_{ij}^{(t)} \) has the maximum value for the cluster \( I \), then vector \( X_j \) is assigned to the class-\( C \).

2.7 Heartbeat recognition

Real ECG data from the cardio-care unit has been used at this stage for decision making. The class of accepted ECG beat is recognised using the following steps:

1. Accept a feature vector \( I_i \) (for an ECG beat) from the ECG of the subject.

\[ I_i = \begin{bmatrix} I_{i1} \\ I_{i2} \end{bmatrix} = \begin{bmatrix} \text{MTE} \\ S \end{bmatrix} \tag{24} \]

2. Measure the Euclidean distance between the feature vector \( I_i \) and cluster centre of each class.

3. If the measured Euclidean distance has the minimum value among all its classes, then the feature vector \( I_i \) will be recognised as the corresponding heartbeat case.

4. Follow steps (1)–(3) for all test vectors.

3 Results and discussion

For the performance analysis of ECG beat detection, we used statistical measures given in (25)–(27). To measure the performance of beat classification we used additional statistical measure given in (28).

Detection Error Rate (DER) = \( (\text{FN} + \text{FP}) / (\text{TP} + \text{FN}) \) \tag{25}

Sensitivity (Se) = \( \text{TP} / (\text{TP} + \text{FN}) \) \tag{26}

Positive Prediction Rate (+P) = \( \text{TP} / (\text{TP} + \text{FP}) \) \tag{27}

Diagnostic Accuracy (DA) = \( \text{Correctly Diagnosed Beats}/\text{Total Beats} \) \tag{28}

QRS detection algorithm (PTE) has been tested with three

| Total records | T.P. (beats) | FN (beats) | FP (beats) | FN + FP (beats) | Se, % | +P, % | DER, % |
|---------------|-------------|------------|------------|----------------|-------|-------|-------|
| 49            | 119375      | 177        | 154        | 331            | 99.85 | 99.87 | 0.27  |
different types of database: mitdb-45 records, ahaadb-2 records and edb-2 records. Sampling frequency for mitdb is 360 Hz whereas for ahaadb and edb it is 250 Hz. In this method, probability of false positives of QRS has been reduced substantially because of polarisation of TE. Table 1 summarises the QRS detection results. Fig. 6 shows the QRS detection by PTE algorithm for the record mitdb-233 (for 20 000 samples).

Further, the ECG time series has been segmented into ECG beats, with reference to R-peaks. Fig. 7 shows the segmented ECG records of the MIT-BIH database. It shows the segments of five different types of ECG beats: NORM, PVC, PACED, LBBB and RBBB.

**Scatter plot:** The approach of using the features with linear relationship, revealed by (17) fulfills the system design requirement of limited number of features. Thus, feature vector for each beat consists of only two features: MTE and S. Scatter plot of these two features of ECG beats from a few MIT-BIH records, for five different classes – NORM, PVC, PACED, LBBB and RBBB, is as shown in Fig. 8. The range of feature values computed for various ECG beats, with reference to R-peaks. Fig. 7 shows the segmented ECG records of the MIT-BIH database records used in this work is as given in Table 2.

A total of 39682 beats were used to evaluate the classification performance of the algorithm, out of which 17774 were of normal beats and 21908 arrhythmia beats. The arrhythmia beats consist of PVC (3339), PACED (3632), LBBB (8075) and RBBB (6862). For the details of classification results, the ‘confusion matrix’ has been given in Table 3. Table 4 illustrates classification performance of the proposed method using the MIT-BIH database. The algorithm correctly classified 39261 beats, yielding 98.93% diagnostic accuracy. The proposed method has been compared with some similar methods, as shown in Table 5. From Table 5 it is clear that Kamath [32] achieved over 95% diagnostic accuracy using only two features. In Kamath’s method, ECG beats are classified using ‘TE in time domain’ against ‘TE in frequency domain’. In the proposed method, the beats are classified using ‘TE in time domain’ (MTE) against ‘informational entropy’ (S). Kamath’s method used Hilbert-transform-based QRS detector, whereas the proposed method used the PTE algorithm. Beats have been classified using neural network classifier in Kamath’s method. Although it is a fast method, it is clear from the scatter plot shown in [32] that it is suitable for separating normal and arrhythmic beats. Scatter plot shown in Fig. 8 clearly shows that the clusters of different classes must be discriminated in order to make the

| Table 3 | Matrix confusion for the classification results |
|---------|----------------------------------------|
| Desired class | NORM | PVC | PACED | LBBB | RBBB |
| NORM | 17676 | 22 | 23 | 25 | 28 |
| PVC | 21 | 3290 | 18 | 18 | 17 |
| PACED | 17 | 21 | 3580 | 21 | 19 |
| LBBB | 19 | 25 | 21 | 8012 | 19 |
| RBBB | 21 | 23 | 21 | 22 | 6796 |

| Table 4 | Beat classification performance analysis |
|---------|----------------------------------------|
| Beat type | Total beats | TP | FP | FN | Se, % | +P, % |
| NORM | 17774 | 17 676 | 78 | 98 | 94.44 | 99.56 |
| PVC | 3339 | 3265 | 91 | 74 | 97.78 | 97.28 |
| PACED | 3632 | 3554 | 83 | 78 | 97.85 | 97.71 |
| LBBB | 8075 | 7991 | 86 | 84 | 98.95 | 98.93 |
| RBBB | 6862 | 6775 | 83 | 87 | 98.73 | 98.78 |
| total | 39 682 | 39 261 | 421 | 421 | 98.93 | 98.93 |

| Table 5 | Comparison of proposed work with some other methods |
|---------|----------------------------------------|
| Method | Beat detector | Beat classifier | No. of features | Performance, % |
| Yeh et al. (17) | DOM | FCM | 4 | Se > 90.35, DA = 93.57 |
| Kamath [32] | Hilbert transform | ANN | 2 | Se = 80, DA = 95 |
| Pal and Mitra [33] | wavelet transform | binary coding | 6 | Se = 97.37, DA = 97.38 |
| Zidelmal and Amirou [2] | wavelet transform | SVM | 7 | Se = 99, – |
| proposed PTE | FCM | 2 | Se = 98.93, DA = 98.93 |

| Table 6 | Comparison of processing time for different applied methods |
|---------|----------------------------------------|
| Method (combination) | Average CPU time (s) to process 30 min record |
| Detector | Classifier | Detection | Classification | Total |
| PTE | FCM | 6.50 | 4.95 | 11.45 |
| DOM | FCM | 22.50 | 4.95 | 27.45 |
| wavelet | ANN | 30.60 | 2.10 | 32.70 |
| wavelet | SVM | 30.60 | 6.30 | 36.90 |
decisions, like a human and not like a machine. In the proposed method the FCM clustering technique has been used to achieve better accuracy. Although it is a little slower, the time consumed by it has been compensated in feature extraction. Another fast method of classification using binary coding has been presented by Pal [32]. It used six features extracted using the wavelet transform method, which limits its speed. Other methods in Table 4 use more than four features. For the low-cost system design, because of limited system resources these methods would offer delay in feature extraction. Hence the system may become unreliable under such circumstances. The routine of the proposed algorithm has been implemented in Matlab. Intel’s Core Two Duo at 3.0 GHz, with 2 GB of RAM has been used to perform various experiments, for measurement of computation time. The average time taken for the algorithm for detection of QRS is about 30% of that of the well-known wavelet transform method, achieving the desired computational efficiency. Table 6 shows the average CPU time for detection and classification of beats of a 30 min long record from the MIT-BIH database. In future, implementation of the algorithm using low-cost ‘Tablet Phone’ under ‘Android’ platform will be a cost effective solution for clinical diagnostic support. The authors are currently working towards it.

The system takes an unknown ECG as input and classifies this into one of five classes – NORM, PVC, PACED, LBBB and RBBB. To investigate the performance of the system with ECG beats of real subject, the ECG measured by cardio-care unit has been applied to the algorithm. Lead II of 20 subjects in the age group 20–50 has been tested. A total of 1874 beats have been recognised. Out of these, 1842 beats classified correctly whereas 32 classified falsely. Thus, classification accuracy of the system with ECG data measured using cardio-care unit for the real subjects is 98.29%. This is comparable to the classification performance using the MIT-BIH database. Fig. 9 shows the photograph of PCB of the cardio-Care unit, and ECG of a 24 year old male subject measured with it on a DSO.

4 Conclusion

In this paper, we presented the complete low-cost system design for ECG beat classification and recognition. To make the system cost effective and yet reliable, constraints on the system resources offered several limitations on design issues such as number of features selected for the classification, feature extraction method and type of classifier used. Owing to the linear relationship between MTE and S, it appeared as the best possible combination to classify ECG beats. There has been substantial reduction in processing time because of the PTE method of QRS detection. Although there are several classifiers available for classification, FCM is the most suitable for the proposed system because of its accuracy. In spite of several limitations, the system achieved very good results with sensitivity, positive prediction rate and diagnostic accuracy of 98.93% each. Owing to these facts, the proposed system is useful for medical diagnostic support in remote and financially weaker regions of low and middle income countries.

5 Acknowledgment

This work was funded by, Center of Excellence of COMMBEDDED SYSTEMS “Hybridization of communications & Embedded Systems” Under TEQIP 1.2.1. The authors are thankful to coordinator Dr. A. G. Keskar.

6 References

1 World Health Organization: (November 2008) Cardiovascular diseases. Available: http://www.who.int/cardiovascular_diseases/en/ 2012, accessed April 2012.
2 Zidelmal, Z., Amirou, A.: ‘Heartbeat classification using support vector machines (SVMs) with an embedded reject option’, Int. J. Pattern Recognit. Artif. Intell., 2012, 26, (1), pp. 1–17
3 Nurettin, A.: ‘A support vector machine classifier algorithm based on a perturbation method and its application to ECG beat recognition systems’, Expert Syst. Appl., 2006, 31, (1), pp. 150–158
4 Ubeysi, E.D.: ‘ECG beats classification using multiclass support vector machines with error correcting output codes’, Digital Signal Process., 2007, 17, (2007), pp. 675–684
5 Lannoy, G., Francois, D., Delbeke, J., Verleyesen, M.: ‘Weighted conditional random fields for supervised inter-patient heartbeat classification’, IEEE Trans Biomed. Eng., 2012, 59, (1), pp. 241–247
6 Can, Y., Vijaya Kumar, B.V.K., Cobmra, M.: ‘Heartbeat classification using morphological and dynamic features of ECG signals’, IEEE Trans. Biomed. Eng. 2012, 59, (10), pp. 2935–2941
7 Chazal, P., O’Dwyer, M., Reilly, R.: ‘Automatic classification of heartbeats using ECG morphology and heartbeat interval features’, IEEE Trans. Biomed. Eng., 2004, 51, (7), pp. 1196–1206
8 Conforto, S., Laudani, A., Oliva, F., Fulginesi, F.R., Schmid, M.: ‘Classification of ECG patterns for diagnostic purposes by means of neural networks and support vector machines’. Proc. 36th Int. Conf. on Telecommunications and Signal Processing (TSP), 2013, Rome, Italy, July 2013, pp. 591–595
9 Facchin, M., Saced, A., Bulusu, S., et al.: ‘A patient-adaptive profiling scheme for ECG beat classification’, IEEE Trans. Inf. Technol. Biomed., 2010, 14, (5), pp. 1153–1165
10 Ince, T., Kiranyaz, S., Gabbouj, M.: ‘A generic and robust system for automated patient-specific classification of ECG signals’, IEEE Trans. Biomed. Eng., 2009, 56, (5), pp. 1415–1426
11 Ivarado, A., Lakshminarayan, C., Prince, J.C.: ‘Time-based compression and classification of heartbeats’, IEEE Trans. Biomed. Eng., 2012, 59, (6), pp. 1641–1648

Fig. 9 Cardio-care unit and an ECG measured with it
12 Ozbay, Y., Ceylan, R., Karlik, B.: ‘A fuzzy clustering neural network architecture for classification of ECG arrhythmias’, Comput. Biol. Med., 2006, 36, (4), pp. 376–388
13 Ceylan, R., Ozbay, Y., Karlik, B.: ‘A novel approach for classification of ECG arrhythmias: type-2 fuzzy clustering neural network’, Expert Syst. Appl., 2009, 36, (3), pp. 6721–6726
14 Osowski, S., Linh, T.H.: ‘ECG beat recognition using fuzzy hybrid neural network’, IEEE Trans. Biomed. Eng., 2001, 48, (11), pp. 1265–1271
15 Guler, I., Ubeyli, E.D.: ‘A novel fuzzy C-means method for classification of premature ventricular contractions using wavelet transform and timing interval features’, IEEE Trans. Biomed. Eng., 2006, 53, (12), pp. 2507–2515
16 Yeh, Y.C., Wang, W.J., Chiou, C.W.: ‘A novel fuzzy C-means method for classifying heartbeat cases from ECG signals’, Measurement, 2010, 43, (10), pp. 1542–1555
17 Melgani, F., Bazi, Y.: ‘Classification of electrocardiogram signals with support vector machines and particle swarm optimization’, IEEE Trans. Inf. Technol. Biomed., 2008, 12, (5), pp. 667–677
18 Hu, Y., Palereddy, S., Tompkins, W.: ‘A patient-adaptable ECG beat classifier using a mixture of experts approach’, IEEE Trans. Biomed. Eng., 1997, 44, (9), pp. 891–900
19 Guler, I., Ubeyli, E.D.: ‘A modified mixture of expert’s network structure for ECG beats classification with diverse features’, Eng. Appl. Artif. Intell., 2005, 18, (7), pp. 845–856
20 Maglaveras, N., Stamkopoulos, T., Diamantaras, K., Pappas, C., Strintzas, M.: ‘ECG pattern recognition and classification using non-linear transformations and neural networks: a review’, Int. J. Med. Inf., 1998, 52, (1–3), pp. 191–208
21 ‘MIT-BIH Arrhythmia Database’, http://www.physionet.org/physiobank/database/mitdb, accessed April 2012
22 ‘Driven-right-leg circuit design’, IEEE Trans. Biomed. Eng., 1983, BME-30, (1), pp. 62–66
23 Osowski, S., Linh, T.H.: ‘A real-time QRS detection algorithm’, IEEE Trans. Biomed. Eng., 1985, BME 32, (3), pp. 230–236
24 Pan, J., Tompkins, W.: ‘A real-time QRS detection algorithm’, IEEE Trans. Biomed. Eng., 1985, BME 32, (3), pp. 230–236
25 Kaiser, J.: ‘On a simple algorithm to calculate the ‘energy’ of a signal’. Proc. Int. Conf. Acoustics, Speech and Signal Processing, ICASSP 90, New Mexico, April 1990, pp. 381–384
26 Chen, S., Chen, H., Chan, H.: ‘A real-time QRS detection method based on moving-averaging incorporating with wavelet de-noising’, Comput. Methods Programs Biomed., 2006, 82, (3), pp. 187–195
27 Shannon, C.: ‘The mathematical theory of communications, I and II’, Bell Syst. Tech. J., 1948, 27, pp. 379–423
28 Fiorentino, M., Claps, P., Singh, V.: ‘An entropy-based morphological analysis of river basin networks’, Water Resources Res., 1993, 29, (4), pp. 1215–1224
29 Pal, S., Mitra, M.: ‘Detection of cardiac arrhythmic beats by logical classifier using binary coding’, IET Sci. Meas. Technol., 2012, 6, (6), pp. 449–455