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ECG beat classification using features extracted from Teager energy functions in time and frequency domains

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Abstract: It is hypothesised that a key characteristic of ECG signal is its non-linear dynamic behaviour and that the non-linear component changes more significantly between normal and arrhythmia conditions than the linear component. This study makes an attempt to analyse ECG beats from an energy point of view by accounting for the features derived from non-linear component in time and frequency domains using Teager energy operator (TEO). The key feature of TEO is that it models the energy of the source that generated the signal rather than the energy of the signal itself. Hence any deviations in the regular rhythmic activity of the heart get reflected in the Teager energy function. To show the validity of appropriate choice of features, *t*-tests and scatter plot are used. The *t*-tests show significant statistical differences and scatter plot of mean of Teager energy in time domain against mean of Teager energy in frequency domain for the ECG beats evaluated on selected Manipal Institute of Technology–Beth Israel Hospital (MIT–BIH) database, which reveals an excellent separation of the features into five different classes: normal, left bundle branch block, right bundle branch block, premature ventricular contraction and paced beats. The neural network results achieved through only two non-linear features exhibit an average accuracy that exceeds 95%, average sensitivity of about 80% and average specificity of almost 100%.

1 Introduction

The issue of selecting an optimal set of relevant features plays an important role in pattern classification. When we perform pattern classification, to meet higher accuracy it is not adequate if we have the best pattern classification system. It is found that performance of most classifiers deteriorates when some of the selected features are redundant. This can happen, for example, when selected features are correlated. The selected features must be capable of separating the classes at least to some useful degree. Otherwise they become irrelevant. It is important that the selected features must be screened for redundancy and irrelevancy. Hence it can be concluded that even the extracted feature vector set must be relevant, non-redundant (uncorrelated), significant and informative. Different methods can be used to extract diverse features from the same raw data. Therefore many times pattern classification turns out to be a problem of classification with smallest number of extracted features.

For more than three decades, computer-aided systems have been used for the classification of ECG beats. In designing such systems, the most important aspect is the integration of a suitable feature extractor and a pattern classifier. Mehmet [1] has tried fuzzy-hybrid neural network in classification of |nManipal Institute of Technology–Beth Israel Hospital (MIT–BIH) arrhythmia beats with an accuracy of 93.5%, sensitivity 99.6% and specificity 95.3%. Mehmet also used auto-regressive coefficients, third-order cumulant and wavelet transform variances as features for classification. Mehmet *et al.* [2] have compared two statistical classifiers, Mahalanobis and minimum distance based, with third-order cumulant, wavelet entropy, auto-regressive coefficients as feature vectors. The advantage of these classifiers is that they use only a single iteration for the training step unlike neural networks that require many iterations. They found Mahalanobis classifier to outperform the other with an accuracy of 92.45%, sensitivity 93.81% and specificity 92.26%. A novel method for classification of arrhythmia using a combination of type-2 c-means fuzzy clustering algorithm and neural network is also tried [3]. It is shown that this combination improves the performance of the classifier compared to individual classifiers and has accuracy of about 99%. Murthy *et al.* [4] discuss concepts of minimum phase correspondent (MPC) and signal length being used to separate the normal beats from the premature ventricular contraction (PVC) beats. Parameters of a linear discriminant function obtained from the training of RR interval and signal length of MPC as feature vectors were used for classification. Gholam and Nazeran [5] use morphological and statistical features to classify a wider range of arrhythmia with an accuracy of around 90%. With QRS width chosen as an input feature vector to a linear discriminant classifier O'Dwyer *et al.* [6] achieved an accuracy of 82% in the classification of beats. ECG spectral feature has also been tried to classify the beats using a statistical method known as Anova to arrive at high accuracy results [7]. They used a feature called half-point of the function energy, which represents a frequency that divides the spectrum into two halves, together with other spectral features to classify the beats. Chen and Chen discuss a non-linear trimmed moving average filter to classify QRS complex beats [8] into normal and PVC with accuracy in excess of 99.8%. However, their classification was restricted to only normal and PVC beats. Tsipouras *et al.* [9] devised an arrhythmia classification system based on RR interval only as the feature vector. The method when evaluated using MIT–BIH arrhythmia database exhibited an accuracy of 98%, sensitivity above 85.14% and specificity above 87.60%. Using correlation coefficient and RR interval as feature vectors, ECG beats were classified by Chuang *et al.* [10]. They found the method to be suitable for classification into premature atrial or ventricular beats. Ivaylo *et al.* [11] used QRS morphological descriptors as feature vectors, with matching pursuit algorithms for beat classification exhibited a good accuracy with sensitivity above 90.70% and specificity above 95.50%. However, they had used two ECG leads for their analysis. With signal variation characteristic as the feature vector, beat classification into normal, PVC and fusion beats was done using principal component analysis to achieve high accuracy [12]. They use only six records from MIT–BIH arrhythmia database.

When classifying ECG beats, in the literature, it is observed that more importance has been given to the linear components of ECG. Although the energy of any two tones at different frequencies, but equal amplitude, is same, the energy required to generate the two tones are different. The higher the frequency of the tone more is the energy required to generate the same and Teager energy (TE) reflects this energy. This paper uses the concept of TE function and analyses ECG beats from an energy point of view. It is hypothesised that ECG signal consists of both linear and non-linear components, and that the non-linear component changes more markedly between normal and abnormal conditions than the linear component. To quantify energy changes between normal and abnormal conditions, two features, TE functions, one in time domain (TD) and the other in frequency domain (FD) are derived. TE-based features are widely used in non-linear speech analysis and processing [13–15]. The prime advantage of using TE function is it accounts for the energy of the system that generated the signal and not the energy of the signal itself [16, 17].

ECG analysis usually commences with the ventricular complex, QRS complex, which is the most significant wave. The normal QRS complex is due to the triggering from Sino-atrial (SA) node and proper propagation through the conduction path in the ventricles. Under certain abnormal conditions, it is found that triggering from ectopic centres and blocks in the conduction path change the course of the propagation front and lead to QRS complexes with wide and bizarre waveforms related to PVC and left and right bundle branch blocks (LBBB, RBBB) or ST segment elevation. Such complexes will not be related to a preceding P wave. In this case the signal energy gets spread over a longer duration in time domain. The instantaneous TE tracks this modulated energy and identifies instantaneous amplitude and also corresponding instantaneous frequency. Consequently, disturbances in the site and frequency of impulse generation and conduction path during the rhythmic activity of the heart manifest in the TEO energy function. The ECG arrhythmia data for analysis includes PVC, LBBB, RBBB and paced beats. The results evaluated on MIT–BIH database using neural network with only two non-linear features exhibit an average accuracy that exceeds 95%, average sensitivity of about 80% and average specificity of almost 100%. This is comparable to that obtained by others using a large number of features.

2 Methods and materials

2.1 ECG records

The ECG records used are from MIT–BIH database. The work involved 15 ECG records from normal sinus rhythm database (16265, 16272, 16273, 16420, 16483, 16539, 16773, 16786, 16795, 17052, 17453, 19090, 19093, 19140 and 19830) and 30 ECG records from arrhythmia database (100–109, 111–119, 121–124, 200–223 and 228–234). From each record the modified lead II was only considered for analysis. The resolution is 200 samples per mV. The sampling frequency of normal sinus rhythm data is 128 Hz and that of arrhythmia data is 360 Hz. Each record is 30 min in length. A total of 67 960 beats from MIT–BIH database were analysed. Out of these 55 465 were normal beats from normal sinus rhythm database and 12 495 were arrhythmia beats from arrhythmia database. The arrhythmia beats included 3685 paced beats, 3270 LBBB beats, 2280 RBBB beats and 3260 PVC beats.

2.2 QRS detection

Software QRS detection has been an arena for research for more than three decades [18–21]. This paper uses the QRS detection algorithm proposed by Benitez *et al.* [19]. First the raw ECG is band-pass filtered (0.5–40 Hz) to remove muscle noise, baseline wander and power line interference. It is then differentiated using a three-point central difference filter to remove baseline drift and motion artefacts. The differentiation suppresses lower amplitude P and T waves while enhances QRS complex. Hilbert transform is then applied to the differentiated ECG. The time of occurrence of the peaks in the resulting signal correspond to the times of R peaks. An adaptive threshold is used to detect the R peaks. The Q and S peaks are determined using linear interpolation and second derivative of ECG (slope detection technique) as suggested in [21].

2.3 Teager energy operator (TEO) and non-linear energy function

TEO is a non-linear energy tracking operator widely used in speech applications [13–15]. The specialty of TEO is that it measures the energy of the system that generated the signal based on mechanical and physical considerations rather than the energy of the signal itself [16, 17]. An important property of TEO is that it is characterised by a time resolution that can track rapid changes in the energy (squared product of amplitude and frequency) of the signal. This is attributed to the fact that TEO operation is almost instantaneous as it uses only three samples and hence, is most suitable for real-time applications. Although the energy of any two tones at different frequencies, but equal amplitude, is same, the energy required to generate the two tones are different. The higher the frequency of the tone more is the energy required to generate the same and TE reflects this energy. Besides energy, the operator can track amplitude envelope and instantaneous frequency (as shown below).

It is interesting to note that TE function in TD is almost always positive when the energy modelled by TEO is from a single source. However, when TEO models energy from more than one source the resulting energy function will be negative over some intervals. This property of TE function can be utilised to identify any disturbance in impulse generation and conduction path or any deviations from normal sinus rhythm.

If a signal sample is represented as $x_n = A\cos(\Omega n + \Phi)$, where A is the amplitude, Φ is the initial phase and Ω is the digital frequency in radians/sample and is given by $\Omega = 2\pi f/f_s$, where f is the analogue frequency in Hz and f_s is the sampling frequency in Hz, then as per the TE algorithm the instantaneous energy E_n at a given instant of time n is given by [16]

$$\begin{aligned} E_n &= x_n^2 - x_{n-1}x_{n+1} \\ &= A^2 \sin^2(\Omega) \\ E_n &\simeq A^2\Omega^2 \end{aligned} \tag{1}$$

for small Ω. With $\Omega < \pi/4$ or $f/f_s < 1/8$, the relative error in the last approximation is always less than 11%. From the above equation, it is clear that the instantaneous TE can track modulation energy and identify instantaneous signal amplitude and also corresponding instantaneous frequency. For example, in a normal subject the rhythm originates at the SA node which fires at a rate of normally 60–100 beats/min. If SA node should become diseased or fail to function, then bundle of His has pacemaker cells which fire at an intrinsic rate of 40–60 beats/min. Unlike the usual instantaneous signal energy which is only proportional to squared instantaneous amplitude, TE is proportional to the squared product of both instantaneous amplitude and instantaneous frequency. This new energy measure is therefore capable of responding rapidly to changes in both amplitude and frequency. Consequently, disturbances in impulse generation and conduction path get reflected in the TEO energy.

Much of the earlier work on TEO was carried out by Maragos and his co-workers [22–24]. The original Teager–Kaiser non-linear energy (NE) for discrete time signal $x[n]$ is given by [24]

$$\mathrm{NE}\{x[n]\} = x^2[n] - x[n-1]x[n+1] \tag{2}$$

The average non-linear energy in time domain, ANE_t, is defined as

$$\mathrm{ANE}_t = \frac{1}{N}\sum_{n=0}^{N-1} \mathrm{NE}\{x[n]\} \tag{3}$$

where N is the number of samples in the ECG beat/QRS interval. ANE_t, the mean of the TE function over the QRS interval provides a means for evaluating non-linear component of ECG signal in the time domain. It is advisable to use a window, such as Hanning window, to reduce the artefacts due to edge effects before applying the operator NE in (2).

The above equations represent TD usage of TEO. To apply TEO in the FD, the TD Hanning windowed ECG beat is first transformed to FD by applying discrete Fourier transform (DFT) [13]. Then the equations below are applied to find the TE function and the corresponding mean in FD. If $X[f]$ represents DFT of $x[n]$, then in the FD the above equations get modified as

$$\mathrm{NE}\{X[f]\} = X^2[f] - X[f-1]X[f+1] \tag{4}$$

$$\mathrm{ANE}_f = \frac{1}{N}\sum_{n=0}^{N-1} \mathrm{NE}\{X[f]\} \tag{5}$$

where N is the number of samples in the DFT. ANE_f, the mean of the TE function, provides a means for evaluating non-linear component of ECG signal in the FD.

2.4 Classification

2.4.1 Features for classification, significance tests (t-tests) and scatter plot: Since the TEO captures the energy of the system that generated the original ECG, as mentioned earlier, the TEO energy reflects the abnormalities in the system that generated the ECG signal. In this work mean of TEO energy functions in TD and FD are the selected feature vectors. To assess the use of these parameters individual and pairwise, significance tests (*t*-tests) are performed. To show the efficacy of selected features in separating classes, a scatter plot is used.

2.4.2 Neural network for classification of beats: To show the efficacy of selected features in separating classes, a scatter plot is used. However, since artificial neural networks have proved themselves as proficient classifiers and are particularly well suited for addressing non-linear problems, we chose neural network. In this paper neural network is used as a classifier to identify if a given ECG beat belongs to normal class or one among the arrhythmia class based on the selected feature vectors. The two feature vectors will serve as inputs to the neural network and the class is the target. Given an input, the neural network is expected to identify if the beat is normal or arrhythmic (PVC, paced, LBBB or RBBB). This is achieved through training the neural network by presenting previously recorded inputs and tuning the network to produce the desired targeted outputs.

Once the neural network is set up, the samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. We use a standard feed-forward network with a hidden layer and trained with back-propagation, provided by MATLAB neural network toolbox. The chosen architecture has two inputs, a hidden layer with 15 neurons and 5 outputs. It is shown that the classification performance and accuracy achieved through only two features is comparable to that obtained by others using a large number of features.

3 Results and discussion

Mean of TE function in TD and FD are chosen as features for classification, and the beats in the normal sinus rhythm (15 records) and arrhythmia (30 records) database, in all 45 records, of MIT–BIH are classified. The study has focused on (a) normal (b) PVC (c) LBBB (d) RBBB and (e) paced beats. Some of the ECG records used for analysis have been specified in the respective figure captions together with the range of discrete samples (within parentheses).

Few illustrations of the application of this new approach to normal and some arrhythmia beats are shown in Figs. 1–4. Fig. 1*a* shows an ECG cycle from the normal sinus rhythm record 16272. This ECG cycle is windowed using a Hanning window to reduce the artefacts due to edge effects. The TE function in TD of the windowed ECG is shown in Fig. 1*b*. The TE displays the strong energy required by the ventricles to contract during the QRS interval. It is to be noted that the energy is almost always positive in normal beats. The magnitude spectrum of windowed ECG and the corresponding TE function in FD are shown in Figs. 1*c* and *d*, respectively. The mean of TE functions in TD and FD are, respectively, 0.0052 and 0.0048. The TE in Fig. 1*d* displays the energy of a normal beat in FD and the frequency range of energy concentration is 0–17 Hz.

Fig. 2*a* shows a PVC beat from arrhythmia record 208. Because such beats arise within an ectopic focus within the ventricular muscle, the QRS complex is wide, bizarre and unrelated to the preceding *P* wave. Further, the iso-electric ST segment will be usually absent. The atrial beat that occurred or was about to occur when the PVC happened is usually blocked, but the subsequent atrial beat will occur on time, and be conducted normally. To reduce the artefacts due to edge effects, the ECG beat is windowed using a Hanning window. The TD TE function of the windowed ECG is shown in Fig. 2*b*. The TE in TD shows a good amount of ripple (with negative peaks) during the inverted part of QRS interval and a considerable decrease in the energy from that of the normal. This means there must have been disturbances in impulse generation and/or conduction path. The magnitude spectrum of windowed ECG and the corresponding TE function in FD are shown in Figs. 2*c* and *d*, respectively. The TE in FD shows energy concentration over the range 0–4 Hz. The mean of TE function in TD is 8.7272×10^{-4} and mean of TE function in FD is 0.9182. It is observed that the mean of TE in TD is lower than that of normal beat, whereas the mean of TE in FD is greater than that of normal beat.

Fig. 3*a* shows a LBBB cycle arrhythmia record 111. A broadened QRS complex suggests a bundle branch block, although there are other causes. A tall notched R wave, absence of Q wave and elevation or depression of ST segment are typical indications of LBBB. The corresponding TE function in TD is shown in Fig. 3*b*. The TE in TD shows a heavy ripple (with negative peaks) during the QRS interval and immediately following the QRS interval. There is a considerable decrease in the energy from that of the normal. This again implies that there must have been disturbances in impulse generation and/or conduction path. The magnitude spectrum of windowed ECG and the corresponding TE function in FD are shown in Figs. 3*c* and *d*, respectively. The TE in FD

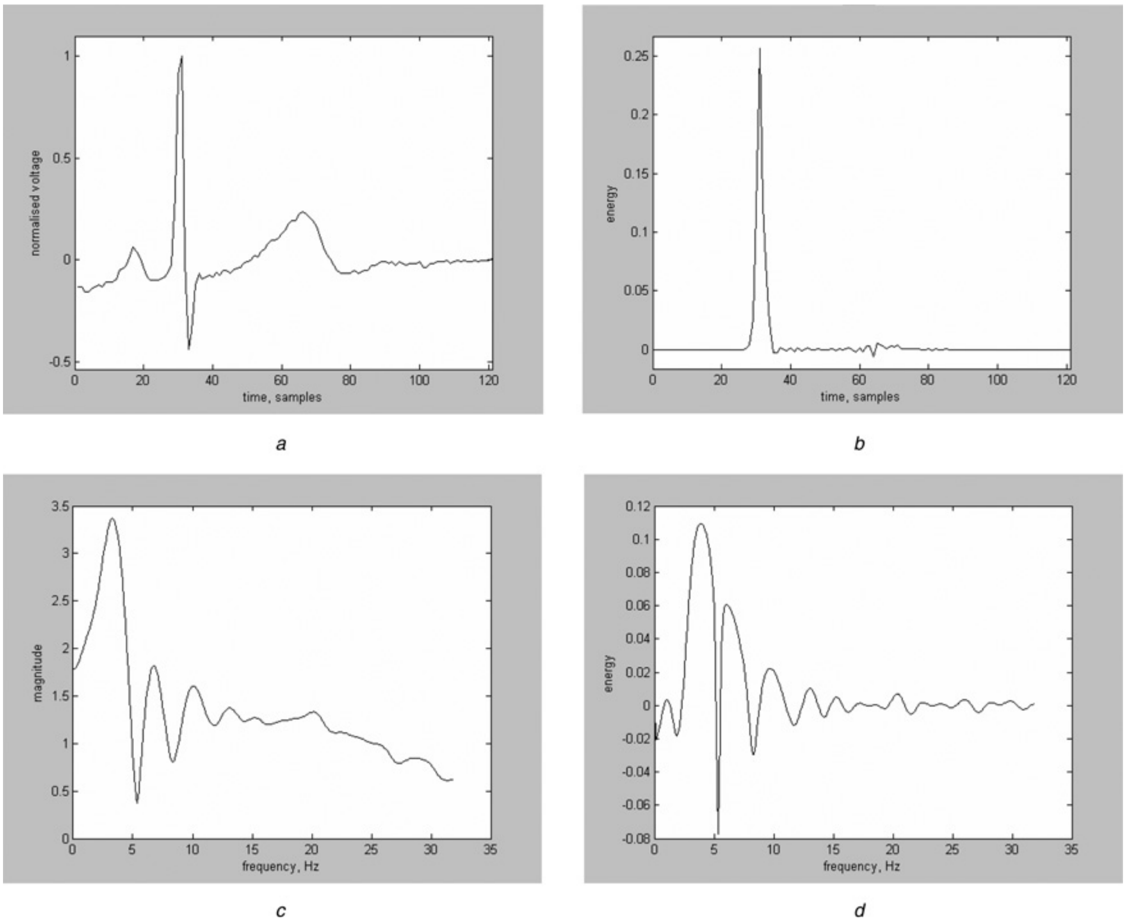

Fig. 1 *Normal ECG beat cycle and corresponding TE function in TD and FD*

a Normal ECG beat 16272(4376:4497)
b TE in TD
c Magnitude spectrum
d TE in FD

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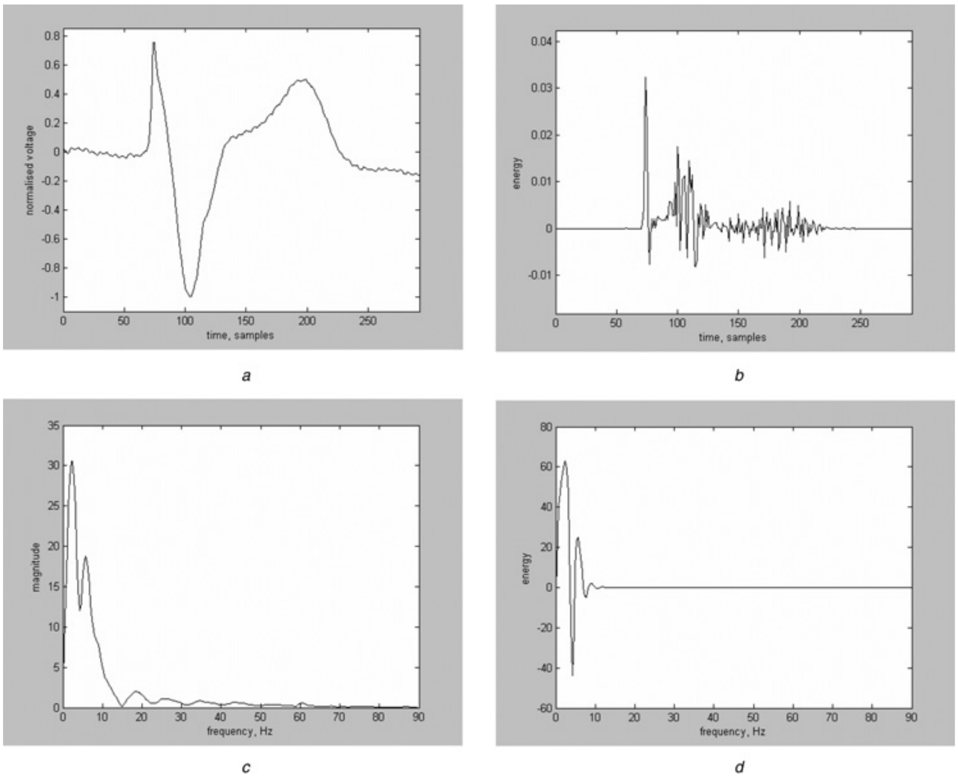

Fig. 2 *PVC ECG beat cycle and corresponding TE function in TD and FD*

a PVC ECG beat 208(10697:10989)
b TE in TD
c Magnitude spectrum
d TE in FD

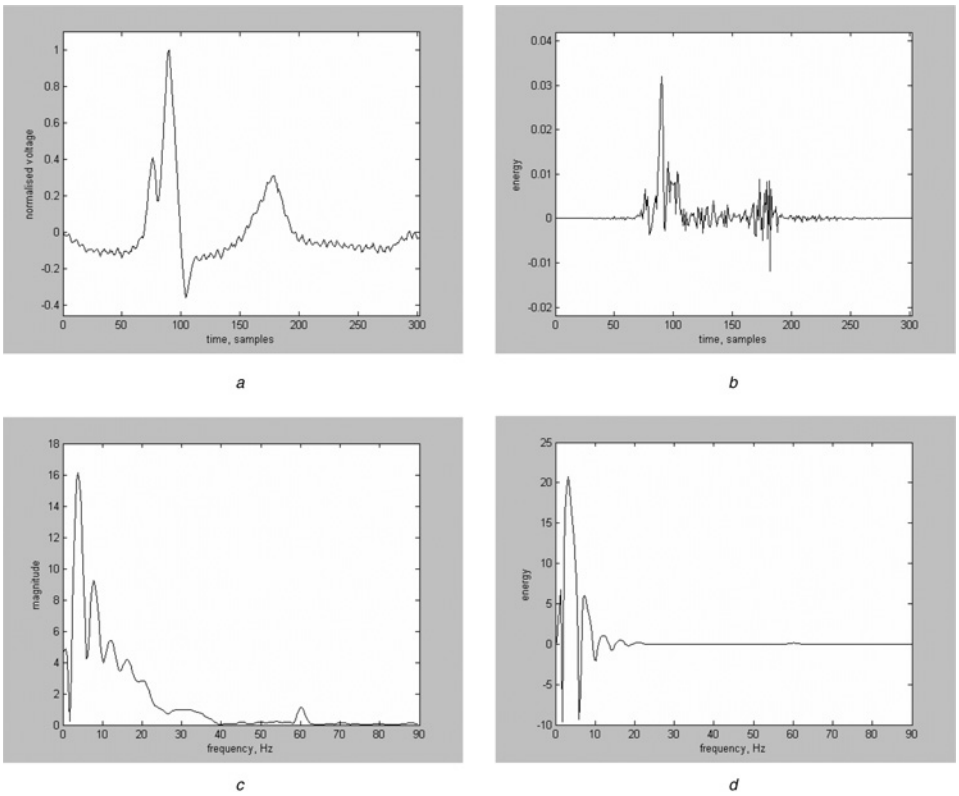

Fig. 3 *LBBB ECG beat cycle and corresponding TE function in TD and FD*

a LBBB ECG beat 111(10881:11183)
b TE in TD
c Magnitude spectrum
d TE in FD

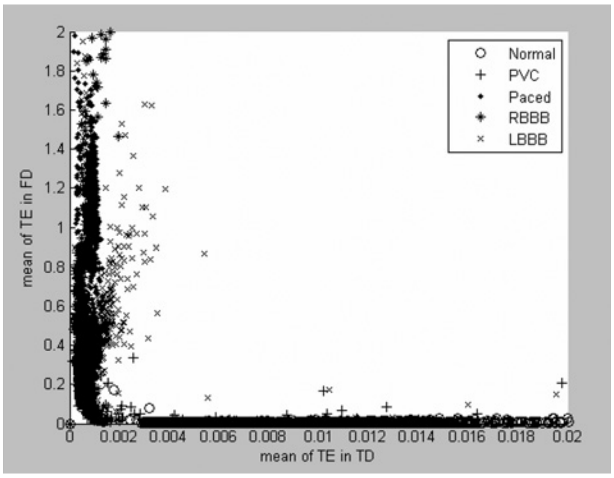

Fig. 4 *Scatter plot of mean of TE in TD against mean of TE in FD*

Table 1 All values are expressed as mean ± SD

Beat type	Mean TE in TD	Mean TE in FD
normal	0.0068 ± 0.0039	0.0029 ± 0.0029
PVC	0.0025 ± 0.0064	0.1703 ± 0.2332
paced	$8.0458 \times 10^{-4} \pm 1.6783 \times 10^{-4}$	0.7333 ± 1.0050
RBBB	$6.8027 \times 10^{-4} \pm 4.5719 \times 10^{-4}$	0.6271 ± 0.4476
LBBB	0.0011 ± 0.0039	0.3773 ± 0.4154

shows energy concentration over the range 2–5 Hz. The mean of TE function in TD is 8.6772×10^{-4} and that of TE function in FD is 0.3439. The statistics of mean values of TE in TD and FD for the different types of ECG beats are tabulated in Table 1.

3.1 Significance tests and scatter plot

From the above discussion and Table 1, it is clear that the mean of TE function in TD for the case of arrhythmia beats is less than that of the normal. However, the mean of TE function in FD for the case of same arrhythmia beats is always greater than that of the normal. As mentioned above, significance tests are performed for each parameter and the results are tabulated in Tables 2 and 3. The results confirm that normal ECG beats are statistically differentiable from arrhythmia beats and that the arrhythmia beats are statistically differentiable among themselves for each of the two features. When we combine the two features in a scatter plot the results exhibit robustness to separate the beats into different classes. Fig. 4 illustrates scatter plot of mean of TEO energy function in TD against mean of TEO energy function in FD, which is used to show the preliminary results of the validity of appropriate selection of features and their impact on the separation of the beats into normal and one of the arrhythmic beats (PVC, paced, LBBB or RBBB). A total of 67 960 beats from MIT–BIH database were analysed. Out of these 55 465 were normal beats from normal sinus rhythm database and 12 495 were arrhythmia beats from arrhythmia database. The arrhythmia beats included 3685 paced beats, 3270 LBBB beats, 2280 RBBB beats and 3260 PVC beats. The plot reveals an excellent separation of the features for normal from those of arrhythmia beats. There is also an excellent discrimination among different arrhythmia beats. This validates the discriminating capability of the selected features for classification of ECG beats.

3.2 Neural network classification results

In practice, a variety of classifiers are available. However, as explained earlier for want of a better classifier, we resorted to neural network. The same ECG records from MIT–BIH were used. In the testing phase out of 26 390 normal beats all were classified as normal beats and out of 6520 arrhythmia beats 1720 beats were incorrectly classified as other beats. The results for accuracy, specificity and sensitivity for the different arrhythmia types are tabulated in Table 4. The results evaluated on MIT–BIH database with only two non-linear features exhibit an average accuracy that exceeds

Table 2 *p*-values and tstat values of *t*-test for mean TE in TD

Beat type	PVC	Paced	RBBB	LBBB
normal	$p = 0$ tstat = 24.26	$p = 0$ tstat = 55.10	$p = 0$ tstat = 47.64	$p = 0$ tstat = 51.16
PVC	–	$p = 0$ tstat = 9.30	$p = 1.1102 \times 10^{-16}$ tstat = 8.43	$p = 4.3222 \times 10^{-8}$ tstat = 5.50
paced	–	–	$p = 0$ tstat = 8.89	$p = 0.0027$ tstat = −3.00
RBBB	–	–	–	$p = 5.0185 \times 10^{-4}$ tstat = −3.48

Table 3 *p*-values and tstat values of *t*-test for mean TE in FD

Beat type	PVC	Paced	RBBB	LBBB
normal	$p = 0$ tstat = −82.53	$p = 0$ tstat = −83.71	$p = 0$ tstat = −160.58	$p = 0$ tstat = −103.78
PVC	–	$p = 0$ tstat = −12.68	$p = 0$ tstat = −21.73	$p = 0$ tstat = −10.77
paced	–	–	$p = 0.0029$ tstat = 2.99	$p = 0$ tstat = 11.99
RBBB	–	–	–	$p = 0$ tstat = 13.60

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Table 4 Percentage specificity, sensitivity and accuracy

Parameters, %	PVC, %	Paced, %	RBBB, %	LBBB, %
specificity	100	99.93	100	100
sensitivity	100	100	98.67	96.67
accuracy	100	99.93	99.90	99.96

95%, average sensitivity of about 80% and average specificity of almost 100%. This is comparable to that obtained by others using a large number of features.

4 Conclusions

The rationale that the key characteristic of ECG signals is its non-linear dynamic behaviour and that the non-linear component changes more markedly between normal and abnormal conditions than the linear component has facilitated the separation of ECG beats into normal and arrhythmia beats. The classification accuracy achieved through only two non-linear features, mean of TEO energy in TD and the mean of TEO energy in FD is comparable to that obtained by others using a large number of parameters.

Since TEO has excellent time resolution, it can capture an energy variation that is directly proportional to square of the product of envelope amplitude and instantaneous frequency [16]. Therefore instead of using just the mean of TE functions in the TD and FD, one can use features extracted from AM–FM estimation. Use of these parameters for the separation of beats into different classes and also diagnosis are being investigated.

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