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QUANTIFICATION OF ELECTROCARDIOGRAM RHYTHMICITY TO DETECT LIFE THREATENING CARDIAC ARRHYTHMIAS USING SPECTRAL ENTROPY

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Abstract

Changes in the normal rhythmicity of the heart may result in different cardiac arrhythmias, which may be fatal or cause serious damage to the heart if sustained over long periods of time. Ventricular tachycardia or fibrillation (VT-VF) as fatal cardiac arrhythmia is the major cause leading to sudden cardiac death. It is crucial for the patient to receive immediate medical intervention when either VT or VF occurs. In this study, we present a novel, and computationally fast method to quantify the rhythmicity of the short-term electrocardiogram (ECG) signals based on spectral entropy feature and there by discriminate between normal sinus rhythm (NSR) and life threatening arrhythmias like, ventricular tachycardia/fibrillation (VT/VF). The receiver operating characteristic curve (ROC) analysis confirms the robustness of this new approach for a window length of 2 s and exhibits an average sensitivity = 99.4% (99.4%), specificity = 98.7% (99.0%), positive predictivity = 98.7% (99.6%), and accuracy = 98.9% (99.2%), to distinguish between normal and VT (VF) subjects. The presented method is simple, highly accurate, computationally efficient, and well suited for real time implementation in automated external defibrillators (AEDs).

Keywords: Electrocardiogram, Spectral Entropy, Ventricular fibrillation, Ventricular tachycardia.

1. Introduction

Ventricular tachycardia (VT) and ventricular fibrillation (VF) are life threatening cardiac arrhythmias as classified in ventricular tachyarrhythmia [1, 2]. It is crucial for the patient to receive immediate medical intervention when either VF or VT occurs.

Nomenclatures

H	Normalized spectral entropy
p_i	Normalized probability density function
$S(f_i)$	Magnitude of spectral component at frequency f_i, V^2Hz^{-1}

Appropriate therapy, however, depends upon correct identification of VT and VF. Despite numerous recent advances in the field of medicine, Ventricular tachycardia/ fibrillation (VT/VF) has been difficult to manage with in clinical practice and mortality rate has remained high. As a consequence the development of new noninvasive methods and measures of mortality risk in VT/VF, including sudden cardiac death, is still a major challenge. The most important determinant in the survival of victims who suffer a cardiac arrest is the length of time between onset of the event and delivery of the defibrillation shock. The American heart association recommends defibrillation response within 5 minutes for out-of-hospital events and 3 minutes for in-hospital events [3]. However, the ANSI/AAMI EC13-1992 standard requires alarms to be activated within 10 s of the onset of abnormal ECG signals [4]. Thus rapid detection and correct classification of these lethal arrhythmias can bring down the rate of mortality from such cardiac diseases. No doubt, appropriate defibrillator discharge at the right time can save the patient. But, inappropriate defibrillator discharge or anti-tachycardiac pacing remains an important clinical problem in implantable cardioverter-defibrillator therapy as they lead to unnecessary pain and sometimes proarrhythmic effects.

As an implication in real time applications the value for specificity is more important than the value for sensitivity or the accuracy (minimal false negative and false positive results) must be high. This can be readily determined from the area under the curve (AUC) of Receiver operating characteristic (ROC) curve (see section 2.3 for details). A wide variety of methods for ECG tachyarrhythmia detection are available in the scientific literature [1-6]. Sequential hypothesis testing of binary sequences has been employed to detect ventricular fibrillation [7]. Though the method shows an improvement over previous methods, the accuracy is not high enough for clinical applications. Baodan Bai et al. use empirical mode decomposition (EMD) to detect ventricular fibrillation. They achieve an accuracy of 99.78%, 99.78% and 100% in separating VT, VF, and NSR, respectively using Bayes theory classifier [8]. However, no reference to the minimum length of rhythms required to distinguish them is made.

EMD functions together with mean signal strength have been used to detect life threatening cardiac pathologies in a sequential algorithm [9]. The authors claim to detect the cardiac abnormalities with good accuracy for episode lengths of 8 s. Several attempts have been made in separating NSR and VT/ VF, in frequency domain and some are mentioned here. Stewart et al. showed that Fourier transform analysis of an 8 s primary (secondary) ventricular fibrillation produced power spectra with a narrow band of frequencies concentrated about the dominant frequency 6 (4) Hz [10]. In the latter case they found that resuscitation success was low compared with the former. The study suggested that higher the frequency of fibrillation beyond 5 Hz, the more is the chance of survival. An integrated framework to assess life threatening arrhythmia has been proposed by Henriques et al. [11]. They use ECG morphology and spectral components as discriminating features and achieve an average sensitivity of 89.3% and specificity of 94.1% for

episode lengths of 10 s. An algorithm called Diagnosis was developed by Barro et al. to classify ECG records into ventricular fibrillation-flutter, ventricular rhythms, imitative artifacts and predominant sinus rhythm based on four parameters computed in frequency domain [12]. Four ventricular fibrillation (VF) detection techniques were compared using recordings of VF to evaluate sensitivity and VF-like recordings to evaluate specificity by Clayton et al. [13]. The techniques included threshold crossing intervals (TCI), autocorrelation function, signal content outside the mean frequency, and signal spectrum shape. They found that the TCI algorithm performed the best with an overall sensitivity of 93 per cent and specificity of 60 per cent. The spectrum, VF filter and ACF algorithms had overall sensitivities of 80, 93 and 87 per cent, and overall specificities of 60, 20 and 0 per cent, respectively. Rosado et al. combined time and frequency domain parameters in their VF detection algorithm to discern between VF and non-VF rhythms with a sensitivity of 86% and specificity of 94.3% [14].

Spectral analysis of life threatening arrhythmias has been carried out by applying Fourier transform on 10 s ECG epochs [15]. It was found that spectral characteristics together with morphology parameters facilitate separation of shockable and non-shockable arrhythmia. Amann et al. studied the reliability of old and new ventricular fibrillation detection algorithms for AEDs [16] and proposed a better algorithm, signal comparison algorithm (SCA), which has an AUC = 0.87 with an overall sensitivity of 72.4 per cent and specificity of 98.0 per cent for episode lengths of 8 s.

Many of the current algorithms, which use classical signal processing techniques to differentiate these rhythms, require more than 5 s of data [17]. We employ spectral entropy to quantify the information content in the rhythmicity of NSR, VT, and VF rhythms. Spectral entropy has been widely used, mostly in speech recognition [18, 19]. It is also employed as electroencephalographic measure of anaesthetic drug effect [20, 21]. This is the first time spectral entropy is used as a feature of rhythmicity to separate NSR from VT/VF. The rationale behind the application of spectral entropy feature is that (1) it is suitable for short widowed segments (of length 2s) of the ECG signal and (2) NSR, VT, and VF are rhythms belonging to different nonlinear physiological processes and hence the probability density functions of the power spectra of the three rhythms are characteristically different. Receiver operating characteristic (ROC) plots used show the efficacy of the spectral entropy feature in discriminating normal from VT/VF subjects.

2. Methods and Materials

2.1. Clinical data

All the ECG records used are from the benchmark PhysioNet databases [22]. This work involved 18 long-term ECG records from normal sinus rhythm (NSR) database (nsrdb) and ECG records of 35 subjects who experienced episodes of sustained ventricular tachycardia, ventricular flutter and ventricular fibrillation (VT/VF) from Creighton University ventricular tachyarrhythmia database (cudb). Each VT/VF record contains 127,232 samples (slightly less than 8.5 minutes). Further, in these records, the minimum number of non-VF beats prior to the onset of a VF episode is 61. The mean time interval from the beginning of the record to the onset of VF is 5 minutes and 47 seconds. The NSR database includes 5 men, aged

26 to 45 years, and 13 women, aged 20 to 50 years. The age and gender of subjects in VT/VF database are not available. In order to arrive at the discriminating thresholds and verify their effectiveness in separating into normal and VT/VF the complete data set is divided into two subsets, training and testing. The NSR database is divided into two groups, first with 9 ECG records (Normal-1) and second, also, with 9 ECG records (Normal-2). Likewise, the VT/VF database is divided into two groups, first with 15 ECG records (VT/VF-1) and second also with 15 ECG records (VT/VF-2). Thus, training database comprises Normal-1 and VT/VF-1, while testing database comprises Normal-2 and VT/VF-2.

From each record the modified limb lead II is only considered for analysis. The resolution is 200 samples per mV for nsrdb and 400 samples per mV for cudb. The sampling frequency of normal sinus rhythm signal from NSR is 128 Hz and that of VT/VF signal from cudb is 250 Hz. Since the sampling frequency does influence upon the calculated indices it is necessary to have the same sampling frequency for all the records. For this reason ECG signals from NSR database are first re-sampled at 250 Hz. Each record is filtered using a 40 Hz low pass filter to remove noise from the 50 Hz or 60 Hz mains interference and in particular, providing enough wideband to incorporate VF spectral terms. A detrending operation is also performed to remove the baseline wandering and a zero mean series is obtained. Then each record is divided into segments of equal time duration (2 s), with 500 samples/ segment in both normal sinus rhythm and VT/VF database. Each segment is windowed using Hanning window before the application of Fast Fourier transform (FFT) to reduce edge effects. We use 1024-point discrete Fourier transform (DFT). A total of 82,650 segments from normal sinus rhythm and from VT/VF data base, each, are analysed.

2.2. Spectral entropy as a measure of rhythmicity

In order to obtain spectral entropy feature, first the Fourier spectrum and then the spectral energy is computed for each segment [18]. Next the probability density function for the spectrum is estimated by normalization over all the frequency components as below:

$$p_i = S(f_i) / \sum_k S(f_k) \qquad \text{for } 1 \leq i \leq n \text{ and for } 1 \leq k \leq n \tag{1}$$

where, p_i is the probability density corresponding to frequency component f_i, $S(f_i)$ is the spectral energy for the same frequency component, and n is the total number of frequency components in the FFT. The corresponding spectral entropy is defined as

$$H = - \sum_i p_i \log_2 (p_i) \qquad \text{for } 1 \leq i \leq n \tag{2}$$

A perfect sine wave has only one nonzero spectral component centered at its fundamental frequency, which is normalized to 1 in the probability density function, after the normalization process. This gives the minimal value for the spectral entropy of zero. Other similar frequency profiles with the spectral energy at specific frequencies, will lead to correspondingly lower values for spectral entropy. By contrast, true white noise will have spectral energy distributed over the entire range of frequencies, with a flat spectrum. This gives the maximal value for the spectral entropy of one. We use spectral entropy as a measure of rhythmicity. A larger value of H implies lower rhythmicity and a smaller value implies a higher rhythmicity.

2.3. *t*-Tests and receiver operating characteristic (ROC) analysis

The statistical differences between the spectral entropy values of normal and VT/VF groups are evaluated using non-paired and pair-wise significance tests (Student's *t*-tests). In case of significant differences between groups, the discriminative performance of the spectral entropy analysis into normal from VT/VF subjects is assessed using receiver operating characteristic (ROC) plots in terms of the area under ROC curve (AUC). ROC curves are obtained by plotting sensitivity values (which represent the proportion of the patients with diagnosis of VT/VF who test positive) along the *y*-axis against the corresponding (1-specificity) values (which represent the proportion of the correctly identified normal subjects) along the *x*-axis by varying the critical threshold value in the decision stage of the algorithm. The ROC curve represents the probability of a true positive result against the probability of a false positive result for all possible values of threshold. Accuracy is a related parameter that quantifies the total number of subjects (both normal and VT/VF) precisely classified.

The AUC measures this discrimination, that is, the ability of the test to correctly classify those with and without the disease and is regarded as an index of diagnostic accuracy. The optimum threshold is the cut-off point in which the highest accuracy (minimal false negative and false positive results) is obtained. This can be determined from the ROC curve as the closet value to the left top point (corresponding to 100% sensitivity and 100% specificity). An AUC value of 0.5 indicates that the test results are better than those obtained by chance, where as a value of 1.0 indicates a perfectly sensitive and specific test. With values of AUC between 0.90 and 1.0, the precision of the diagnostic test is considered to be excellent; with values between 0.8 and 0.89, it is good; with results between 0.70 and 0.79, it is treated fair; with the values in the range 0.60 to 0.69 the precision is poor and for values between 0.50 to 0.59 it is considered as bad.

3. Results and Discussion

To test for significance of spectral entropy feature, first we compare the entropy features of the ECG data from normal and VT/VF subjects of training database. Next, we validate our approach conducting another case study on normal and VT/VF subjects from testing database. The ECG records of the NSR and VT/VF databases are pre-processed and segmented as mentioned in Sec. 2.1. Spectral Entropy is analyzed from segments of 2 s (500 samples) over the entire recording period. In this study we did not separate VT and VF, since this decision is not required for defibrillators [23].

The rhythm morphologies of three types of ECG signals, NSR episode, VT episode and VF episode are shown in Fig. 1. All the signals are plotted with respect to same time scale (in samples). It can be observed that the widths of the QRS complexes are different in the three signals. For NSR the QRS width is usually in the range 0.06-0.1 sec, and for VT the QRS complex is much wider (> 0.1 sec). In VF, no QRS complexes are seen. Further, in the case of NSR P waves are normal, while in the case of VT/ VF no P waves are seen. Figure 2 shows the respective periodograms of the same ECG signals, NSR episode, VT episode and VF episode, shown in Fig. 1. All the power spectra are plotted with respect to same frequency scale (in Hz). The NSR episode being a broad band signal shows

energy concentration up to about 30 Hz, and the VT episode has energy concentration up to about 20 Hz. The VF episode has energy concentration only in the range 0-10 Hz. It is interesting to see that the spectral energy peaks of NSR are much smaller than those of VT and VF and the spectral energy peaks of VT are smaller than those of VF. It can be readily observed that all the three power spectra are characteristically different.

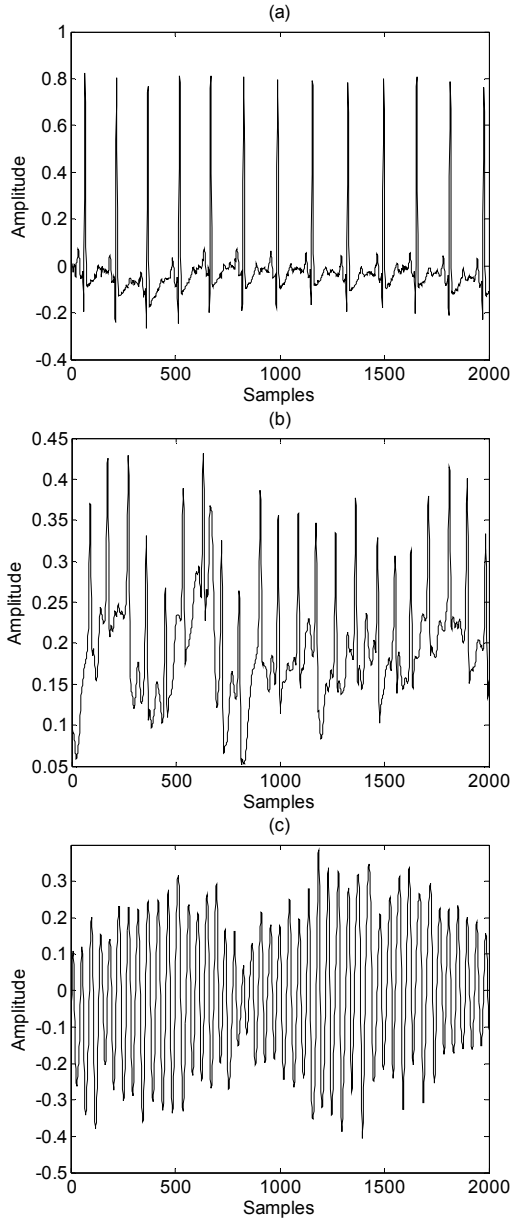

Fig. 1. Rhythm Morphologies of Three Types of ECG Signals from Training Database. (a) NSR Episode, (b) VT Episode and (c) VF Episode.

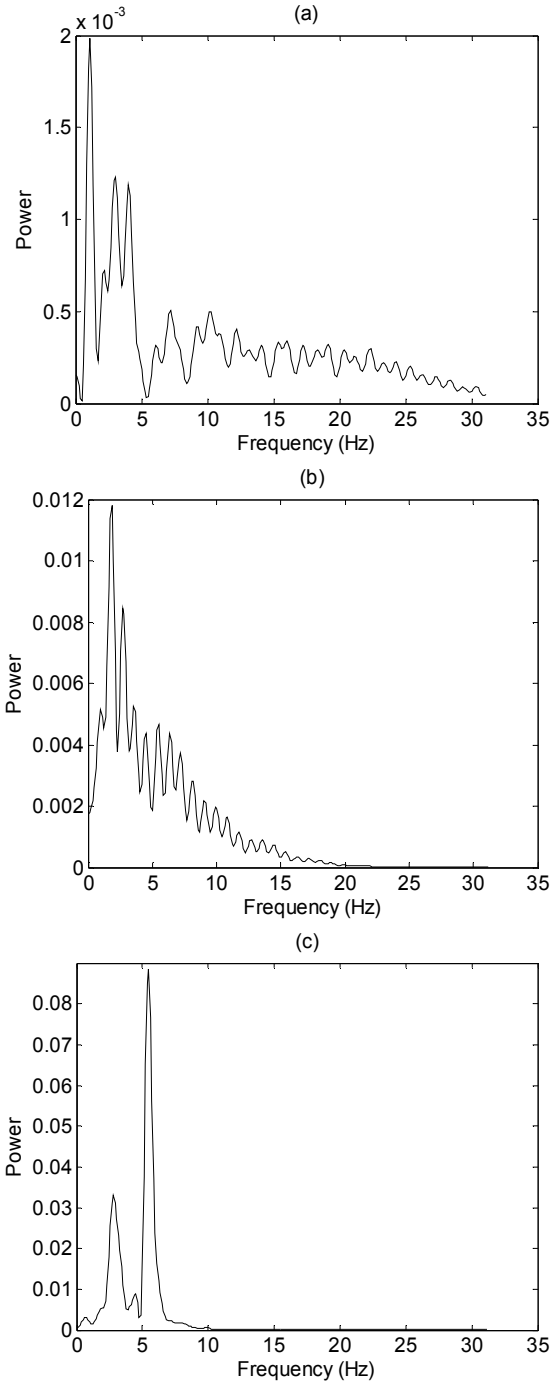

Fig. 2. Periodograms of the same ECG Signals shown in Fig. 1. (a) NSR Episode, (b) VT Episode and (c) VF Episode.

The distribution of spectral entropy values, for the NSR, VT and VF classes (training database) are shown using Box-whiskers plots in Fig. 3(a). The boxes (inter-quartile range) and also the whiskers of normal and VT/VF subjects are non-overlapping. But, the boxes of VT and VF classes of training database overlap. This implies that spectral entropy can be used to distinguish between normal and VT/VF subjects. The results of statistical analysis of non-paired Student's *t*-test for normal, VT and VF groups of training database are depicted in Table 1. All values are expressed as mean ± Standard Deviation (median) [95% Confidence Interval]. For normal subjects of training database, we find the following spectral entropy (mean ± S.D.): 0.7528 ± 0.0163. For VT subjects we find the following spectral entropy (mean ± S.D.): 0.5561 ± 0.0277, different from normal. For VF subjects we find the following spectral entropy (mean ± S.D.): 0.5039 ± 0.0252, different from normal. These distributions show that spectral entropy is sufficient to distinguish between normal and VT/VF subjects of training database. It is found that spectral entropy for VT/VF group is always smaller than that of the normal group. This implies an increase in the rhythmicity of VT/VF group compared to normal group, the rhythmicity of VF being higher than that of VT.

Table 1. Descriptive Results of Spectral Entropy Analysis for Training Group. All Values are Expressed as Mean ± SD (Median) [95% CI]. (Non-paired Student's *t*-test; $p < 0.0001$)

Subject	spectral entropy
NSR	0.7528 ± 0.0163 (0.752) [0.7506 0.7541]
VT	0.5561 ± 0.0277 (0.556) [0.5545 0.5596]
VF	0.5039 ± 0.0252 (0.5031) [0.5013 0.5087]

Comparing paired *t*-test results (*p*-value and tstat) from Table 2, it is found that spectral entropy discriminates well NSR from VT/VF. This finding is substantiated using ROC plots, which are shown in Fig. 3(b), with normal and VT (shown by solid line) and normal and VF (shown by dash-dot line). With spectral entropy, in Fig. 3(b), it is found that (i) for normal and VT separation, the area under the curve (AUC) is 0.9944 with sensitivity = 99.4%, specificity = 98.7%, positive predictivity = 98.7%, and accuracy = 98.9% and (ii) for normal and VF separation, the area under the curve (AUC) is 0.9972 with sensitivity = 99.4%, specificity = 99.0%, positive predictivity = 99.6%, and accuracy = 99.2%. At the cut-off point for best sensitivity and specificity, the critical threshold value of spectral entropy to separate NSR from VT in the training database is found to be 0.6843, while that to separate NSR from VF is found to be 0.6603.

Table 2. *p*-Values and tstat (Test Statistic) Values of Paired *t*-test for Spectral Entropy Analysis of Normal and VT/VF Subjects from Training Group.

Subject	VT	VF
NSR	$p = 0$; tstat= 118.2250	$p = 0$; tstat= 133.0937

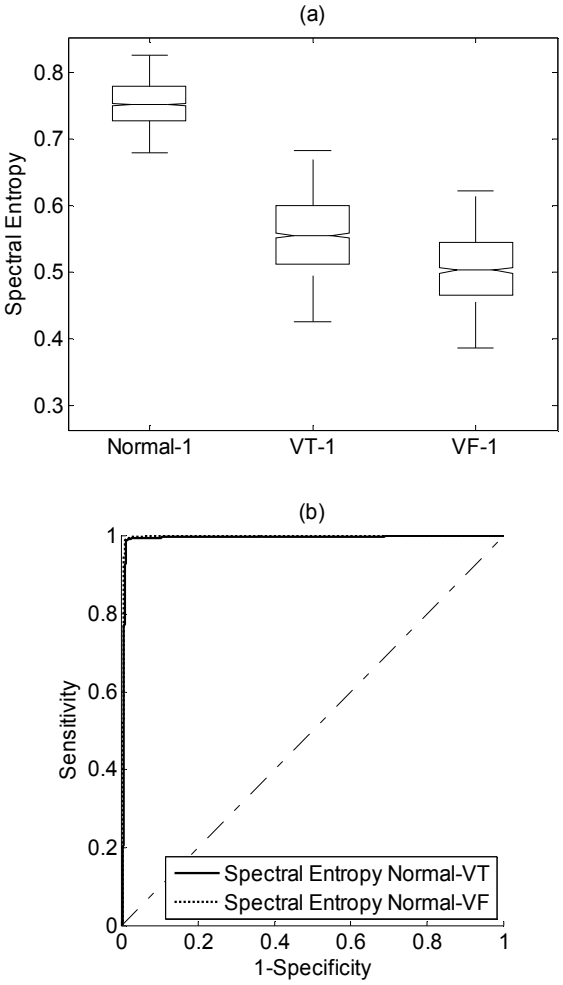

Fig. 3. (a) The Distribution of Spectral Entropy Values Using Box-Whiskers Plots (without Outliers) for Normal, VT and VF Rhythms from Training Database. (b) ROC Curves with Spectral Entropy, for Normal and VT (Solid Line), and Normal and VF (Dash-dot Line).

The diagonal line (dotted line) from 0,0 to 1,1 represents ROC Curve that cannot discriminate between normal and VT/VF from training database.

Figures 4(a) and (b) show, respectively, synthesized ECG signals from training database comprising NSR-VT, and NSR-VF rhythms in sequence, each 7 s (3500 samples) long, together with the corresponding spectral entropy variations. The empirically found critical thresholds (at Th1 = 0.6843 and Th2 = 0.6603 marked by horizontal solid lines in the respective figures) are used for separating NSR and VT/ VF rhythms. For NSR rhythm the spectral entropy is above Th1 (Th2). But with the onset of VT (VF) rhythm the spectral entropy

suddenly falls and remains below Th1 (Th2). Thus, spectral entropy can readily track onset of VT/VF.

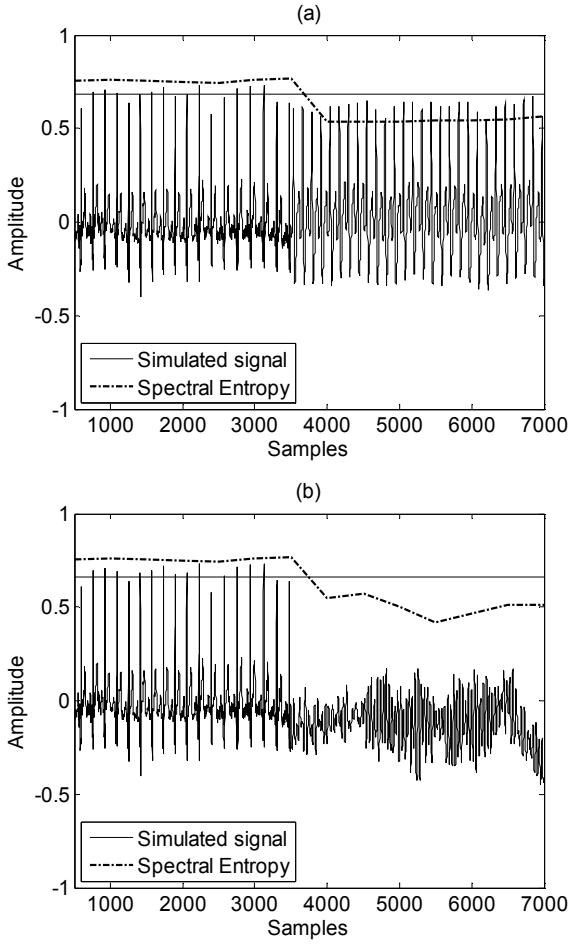

Fig. 4. Variation of Spectral Entropy (dotted line) for a Simulated Signal (Solid Line) Comprising (a) NSR-VT and (b) NSR-VF Rhythms in Sequence from the Training Database.

The horizontal solid lines mark the respective threshold.

Finally, to verify the effectiveness of these discriminating thresholds we conduct another case study on normal and VT/VF subjects from testing database. The distribution of spectral entropy values, for the NSR, VT and VF classes (testing database) are shown using Box-whiskers plots in Fig. 5(a). It is found that the boxes (inter-quartile range) of normal and VT subjects non-overlap. And, the upper whisker of VT and the lower whisker of normal classes overlap. But, both the boxes (inter-quartile range) and the whiskers of normal and VF subjects are non-overlapping. This plot shows that spectral entropy can be used to distinguish between normal and VT/VF subjects.

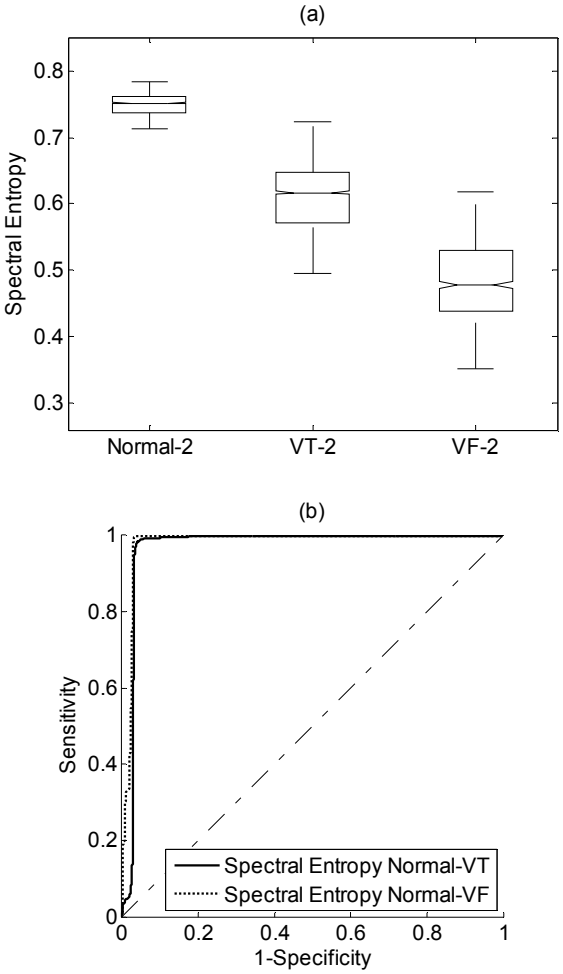

Fig. 5. (a) The Distribution of Spectral Entropy Values Using Box-Whiskers Plots (without outliers) for Normal, VT and VF Rhythms from Testing Database. (b) ROC Curves with Spectral Entropy, for Normal and VT (Solid Line), and Normal and VF (Dash-dot Line).

The diagonal line (dotted line) from 0,0 to 1,1 represents ROC Curve that cannot discriminate between normal and VT/VF from training database.

The results of statistical analysis of non-paired Student's *t*-test for normal and VT/VF groups of testing database are depicted in Table. 3. All values are expressed as mean ± Standard Deviation (median) [95% Confidence Interval]. For normal subjects, we find the following spectral entropy (mean ± S.D.): 0.7509 ± 0.0077. For VT subjects we find the following spectral entropy (mean ± S.D.): 0.6144 ± 0.0245, different from normal. For VF subjects we find the following spectral entropy (mean ± S.D.): 0.4806 ± 0.0292, different from normal. The paired *t*-test results (*p*-value and tstat) are shown in Table 4. The ROC plots for

spectral entropy are shown in Fig. 5(b). It is found that (i) for normal and VT separation, the area under the curve (AUC) is 0.96304 with sensitivity = 97.7%, specificity = 95.2%, positive predictivity = 97.6%, and accuracy = 96.4% and (ii) for normal and VF separation, the area under the curve (AUC) is 0.9805 with sensitivity = 99.3%, specificity = 96.9%, positive predictivity = 90.4%, and accuracy = 97.5%. At the cut-off point for best sensitivity and specificity, the critical threshold value of spectral entropy to separate NSR from VT in the testing database is found to be 0.7024, while that to separate NSR from VF is found to be 0.6712. Both of these values are higher than the corresponding values of the training database. If we are to maintain critical threshold values for the testing dataset, same as those of training set, then it is found that in either case the specificity increases while sensitivity decreases which is exactly what an AED algorithm would want. To be specific, the new sensitivity and specificity values to separate NSR from VT in the testing database are found to be 95.51% and 96.59%, respectively. The new sensitivity and specificity values to separate NSR from VF are found to be 98.92% and 96.94%, respectively. The above results again substantiate our finding that spectral entropy of ECGs discriminates well NSR from VT/VF. The difference in accuracy and other measures of testing database can be attributed to age differences and differing male-to-female ratios between training and testing databases.

Table 3. Descriptive Results of Spectral Entropy Analysis for Testing Group. All Values are Expressed as Mean ± SD (Median) [95% CI]. (Non-paired Student's *t*-test; $p < 0.0001$)

Subject	spectral entropy
NSR	0.7509 ± 0.0077 (0.752) [0.7396 0.7437]
VT	0.6144 ± 0.0245 (0.6171) [0.5975 0.6028]
VF	0.4806 ± 0.0292 (0.4785) [0.4804 0.4903]

Table 4. *p*-Values and tstat (Test Statistic) Values of Paired *t*-Test for Spectral Entropy Analysis of Normal and VT/VF Subjects from Testing Group.

Subject	VT	VF
NSR	p= 0; tstat= 81.7002	p= 0; tstat= 108.2952

Synthesized ECG signals from testing database comprising NSR-VT, and NSR-VF rhythms in sequence, each 7 s (3500 samples) long, together with the corresponding spectral entropy variation are depicted in Figs. 6(a) and (b), respectively. The empirically found critical thresholds of training database (at Th1 = 0.6843 and Th2 = 0.6603 marked by horizontal solid lines in the respective figures) are retained for discriminating NSR and VT/ VF rhythms from testing database. Like in Fig. 4, for NSR rhythm the spectral entropy is always above Th1 (Th2). But when VT (VF) rhythm occurs the spectral entropy suddenly falls and remains below Th1 (Th2). Thus, spectral entropy can keep track of the onset of VT/VF.

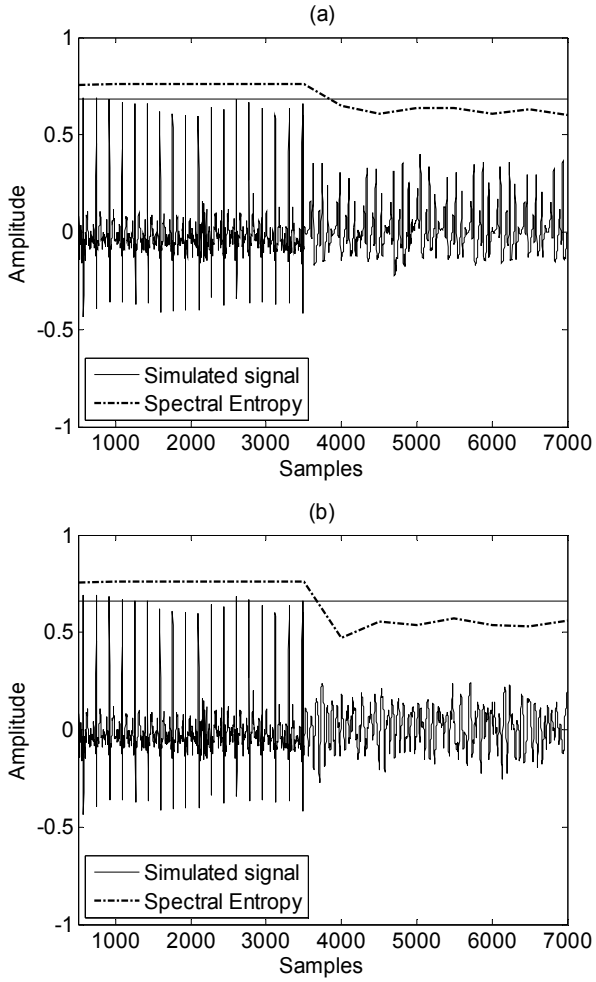

Fig. 6. Variation of Spectral Entropy (Dotted Line) for a Simulated Signal (Solid Line) Comprising (a) NSR-VT and (b) NSR-VF Rhythms in Sequence from Testing Database.

The horizontal solid lines mark the respective threshold (from training database).

The results obtained are reproducible and very promising. The presented method is simple, computationally efficient, and well suited for real time implementation in AEDs. One limitation of the current study is the small sample size. Although we have reported spectral entropy to yield excellent results based on the *p*-value generated from the *t*-statistics, factors like high variance, age differences, and differing male-to-female ratios between groups will have an impact on the results when statistical analyses are carried out on small sample sizes. Nevertheless, the results of this study provide sufficient evidence to warrant the execution of larger studies that can provide more statistically robust confirmation of the application of symbolic dynamics as a reliable measure of cardiac health.

4. Conclusion

The spectral entropy analysis was applied on the windowed nonstationary raw ECG time series from normal and VT/VF subjects. The quantified spectral entropy is found to have potential in discriminating normal and VT/VF subjects and thus can significantly add to the prognostic value of traditional cardiac analysis. This entropy feature can easily be analysed from the automated AED ECG recordings without time consuming pre-processing and hence, are appropriate for practical applications. Appropriate defibrillator discharge at the right time can save the patient. At the same time, inappropriate defibrillator discharge or anti-tachycardiac pacing remains an important clinical problem in therapy as they lead to unnecessary pain and sometimes proarrhythmic effects. To circumvent this problem it is essential that the accuracy (minimal false negative and false positive results) is high (with our algorithm about 99.0%). Many of the current algorithms, which use classical signal processing techniques to differentiate the rhythms, require more than 5 s of data. Using longer record for this kind of analysis is not amenable. Although the ECG data we use contains both 30 minutes and 20 hours duration records, our method tests very short segments, of the order of 2 s duration. Hence the method is well suited for real time implementation in AEDs.

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