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Frequency-domain features for ECG beat discrimination using grey relational analysis-based classifier

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Abstract

This paper proposes a method for electrocardiogram (ECG) heartbeat discrimination using novel grey relational analysis (GRA). A typical ECG signal consists of the P-wave, QRS complexes and T-wave. We convert each QRS complexes to a Fourier spectrum from ECG signals, the spectrum varies with the rhythm origin and conduction path. The variations of power spectrum are observed in the range of 0–20 Hz in the frequency domain. To quantify the frequency components among the various ECG beats, GRA is performed to classify the cardiac arrhythmias. According to the AAMI (Association for the Advancement of Medical Instrumentation) recommended standard, heartbeat classes are recommended including the normal beat, supraventricular ectopic beat, bundle branch ectopic beat, ventricular ectopic beat, fusion beat and unknown beat. The method was tested on MIT–BIH (Massachusetts Institute of Technology–Beth Israel Hospital) arrhythmia database. Compared with other artificial intelligence (AI) methods, the results demonstrate the efficiency of the proposed noninvasive method, and also show high accuracy for detecting ECG signals.

Keywords: Electrocardiogram (ECG); Grey relational analysis (GRA); QRS complex; Frequency domain; Cardiac arrhythmia

1. Introduction

ECG signal is a noninvasive measurement for reflecting the internal status of heart and myocardium electrical activity. By placing electrodes on the body surface, a 12-lead electrocardiograph is used to record the electrical activity. Arrhythmias are not imminently life-threatening but may require therapy to prevent further problems. The sequence of electrical signals provides symptomatic information for classifying cardiac arrhythmias. The measurement devices can record large amounts of signals (Holter ECG). However, they do not automatically classify abnormalities and require offline analysis from the record data. Designing non-invasive method, signal processing, signal recognition, decision support and human computer interface for stationary/portable monitored device has become an assistance tool for pattern-recognition tasks. To ensure accurate detection in clinical investigation, the diagnostic procedure requires automatic classification, high-performance computing and easy implementation for heartbeat recognition [1–3].

In the literature, diagnostic methods have been applied to detection in conjunction with time domain, frequency domain, and time-frequency domain techniques. The QRS complex in ECG signals varies with the origin and the

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conduction path of the activation pulse. Various features from each heartbeat are extracted to detect arrhythmia waveforms. In the time domain, these features are heartbeat interval, amplitude parameters (QRS, ST), duration parameters (QRS, QT, and PR), and combined parameters (Q/R ratio, S/R ratio) [3,4]. When the activation pulse does not travel through the normal conduction path, the QRS complex becomes wide, and the high-frequency components are attenuated. For frequency-based features, frequency spectrum of individual QRS complex is found in the range of 0–20 Hz. The spectrum has a maximum amplitude at 4 Hz in ventricular tachycardia (VT), and its amplitude decreases as the frequency increases [5]. The frequencies of ventricular fibrillation (VF) are concentrated between 4–7 Hz [6]. In the time-frequency technique, wavelet transform (WT) has applied to extract the features of cardiac arrhythmias [1, 2]. These techniques are robust to time-varying signal analysis, but it is not capable of recognition. Applying these symptomatic features, linear discriminates and artificial-intelligent (AI) approaches have been proposed to improve the classification of cardiac abnormalities including wavelet neural networks [1], artificial neural network (ANN) [4, 5,7,8], and fuzzy hybrid neural networks [9,10].

To develop an assistance tool, the diagnostic algorithm must be easy to implement in the virtual instrument technology and hardware device with a compact configuration. The morphology of the QRS complex varies in both normal and abnormal rhythms. Accurate diagnosis is limited by the number of amplitude parameters. The WT is robust to time-varying signal analysis and it can point out occurrence time, but it is not capable of recognition. For the purpose of cardiac arrhythmia classification, ANNs are applied in this study. ANNs are well known for its learning and recognition ability. However, the limitations of ANNs are the training process, determining a possible architecture and network parameters assignment in the clinical environments. Considering these limitations, fast Fourier transform (FFT) is used to estimate frequency spectra. GRA is studied and proposed for heartbeat signal recognition. For adaptation application, the property of the GRA has a function of mathematical operation for processing numerical data or binary data, flexible pattern mechanism with add-in and delete-off features and expandable or reducible without adjusting any parameter.

In this paper, the diagnostic procedure consists of two stages: first, the frequency-based features are computed by FFT; subsequently, the GRA based classifier is used to classify normal and abnormal heartbeats. The heartbeat classes are recommended by AAMI standard. Test data are obtained from MIT–BIH arrhythmia database. The results show computational efficiency and accurate recognition.

2. Problem description

An ECG signal represents the changes in electrical potential during the heartbeat as recorded with noninvasive electrodes on the limbs and chest; a typical ECG signal consists of the P-wave, QRS complex, and T-wave. Cardiac arrhythmias divide into two groups, the first group is life threatening and requires immediate therapy with an automatic external defibrillator (AED) or an implantable cardioverter defibrillator (ICD) [5]. The second group is not life threatening but requires sustainability therapy. QRS complex in ECG signals vary according to the origin and conduction path of the activation pulse in the heart. When the activation pulse originates in the atrium and travels through the conduction path, the QRS complex has a sharp and narrow deflection. After converting each QRS complex to a Fourier spectrum, the spectrum contains high-frequency components. The QRS complex becomes broad and distorted due to the activation pulse originating in the ventricle and not going the conduction path. Frequency-domain analysis applies high-frequency and low-frequency ranges to discriminate ventricular rhythm, atrial rhythm, parasympathetic and sympathetic activity signals. For example, spectral analysis is the linear transform used to diagnose ventricular tachyarrhythmia. Power spectrum of individual QRS complex is found significant differences in the 0–20 Hz frequencies. The spectrum in VT has maximum amplitude at 4 Hz [5]. Spectral analysis is also used in the analysis of heart rate variability (HRV) signals. Power spectra in the 0.15–0.5 Hz ranges reflect respiratory sinus arrhythmias and cardiac vagal activity, baro-receptor control is mediated by vagal and sympathetic systems in the 0.04–0.15 Hz ranges, and very low-frequency ($\leq$0.04 Hz) is related to thermoregulatory, vascular mechanisms and rennin-angio tension systems [7,11].

Fourier analysis (FA) is a method of data analysis. It breaks up a signal into sinusoidal waves of various frequencies. For sampled vector data, FA performs the discrete Fourier transform (DFT). FFT is an algorithm for computing the DFT of a sequence. It is particularly useful in areas including signal and image processing, where its uses range from filtering, convolution and frequency analysis to power spectrum estimation. In this paper, frequency-domain analysis has been used in the applications of signal process. Frequency-based features are computed by FFT, and are

Table 1
Heartbeat classes of human ECG

Heartbeat class	Cardiac arrhythmia	Symbol
Normal	Normal Beat (•)	**Nor**
Ventricular Ectopic Beat	Ventricular Premature Contraction (V)	**VEB**
Supraventricular Ectopic Beat	Atrium Premature Beat (A)	**SEB**
Bundle Branch Ectopic Beat	– Left Bundle Branch Block Beat (L) – Right Bundle Branch Block Beat (R)	**BBEB**
Unknown Beat	– Paced Beat (P) – Unclassified Beat (U)	**UB**
Fusion Beat	– Fusion of Paced and Normal Beat (f) – Fusion of Ventricular and Normal Beat (F)	**FB**

Note: (1) Heartbeat class: AAMI recommended practice.
(2) Cardiac arrhythmia: MIT–BIH arrhythmia database.

used for multiple ECG beat recognition. In this paper, major heartbeat classes are divided into six types according to AAMI recommended practice [3] and the MIT–BIH arrhythmia database (from Record 100 to Record 234) [12] as shown in Table 1. Comparison data and test data are obtained from MIT–BIH arrhythmia database including common arrhythmias. The classifier based on grey relational analysis (GRA) is used for multiple ECG signal classification.

3. Mathematical method

The GRA includes local relation and global relation analysis. It is a method to determine the relation of a discrete data to other sequence data [13,14]. Based on similarity and dissimilarity, the relation is the relational measurement of attribute in different sequences. For certain window duration, each QRS complex is extracted as $V_{QRS} = [v_1, v_2, v_3, \ldots, v_p, \ldots, v_P]$, P is the number of sampled points, $p = 1, 2, 3, \ldots, P$. Frequency spectra are computed by the function *fft*(•) [15,16]

$$X = [\ x_1 \quad x_2 \quad \cdots \quad x_i \quad \cdots \quad x_n\ ] = fft(V_{QRS}). \tag{1}$$

The DFT is found by taking the n-point FFT. The FFT returns a two-sided spectrum in complex form (Real and Imaginary Parts), which can scale and convert to polar form to obtain amplitude and phase. The amplitude of FFT is related to the number of points in the time-domain signal. If X is complex, compute the amplitude of the FFT of a sequence by the function *abs*(•)

$$A = [\ a_1 \quad a_2 \quad \cdots \quad a_i \quad \cdots \quad a_n\ ] = \frac{abs(X)}{\max[abs(X)]}. \tag{2}$$

Each element a_i of A is the absolute value of the corresponding element of X. The element a_i, $i = 1, 2, 3, \ldots, n$, is the selected amplitude of frequency spectrum. Each spectrum is normalized with the maximum amplitude. Suppose a sequence be the test sequence for comparison to other sequences, where the test sequence is $a_i(0)$, $i = 1, 2, 3, \ldots, n$, and K comparative sequence is $A(k) = [a_1(k), a_2(k), a_3(k), \ldots, a_i(k), \ldots, a_n(k)]$, $k = 1, 2, 3, \ldots, K$, can be represented as

$$A_{test} = [\ a_1(0) \quad a_2(0) \quad \cdots \quad a_i(0) \quad \cdots \quad a_n(0)\ ] \tag{3}$$

$$A_{comp} = \begin{bmatrix} A(1) \\ A(2) \\ \vdots \\ A(k) \\ \vdots \\ A(K) \end{bmatrix} = \begin{bmatrix} a_1(1) & a_2(1) & \cdots & a_i(1) & \cdots & a_n(1) \\ a_1(2) & a_2(2) & \cdots & a_i(2) & \cdots & a_n(2) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_1(k) & a_2(k) & \cdots & a_i(k) & \cdots & a_n(k) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_1(K) & a_2(K) & \cdots & a_i(K) & \cdots & a_n(K) \end{bmatrix}. \tag{4}$$

Compute the absolute deviation of test sequence A_{test} and k comparative sequence $A(k)$ by

$$\Delta d_i(k) = |a_i(0) - a_i(k)|. \tag{5}$$

The deviation matrix ΔD can be represented as

$$\Delta D = \begin{bmatrix} \Delta d_1(1) & \Delta d_2(1) & \cdots & \Delta d_i(1) & \cdots & \Delta d_n(1) \\ \Delta d_1(2) & \Delta d_2(2) & \cdots & \Delta d_i(2) & \cdots & \Delta d_n(2) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \Delta d_1(k) & \Delta d_2(k) & \cdots & \Delta d_i(k) & \cdots & \Delta d_n(k) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \Delta d_1(K) & \Delta d_2(K) & \cdots & \Delta d_i(K) & \cdots & \Delta d_n(K) \end{bmatrix}. \tag{6}$$

The grey grades $f(k)$ can be calculated as [17]

$$f(k) = \exp\left[-\xi\left(\frac{\sqrt{\sum_{i=1}^{n}(\Delta d_i(k))^2}}{\Delta d_{\max} - \Delta d_{\min}}\right)^2\right], \quad \xi \in (0, 10) \tag{7}$$

$$\Delta d_{\min} = \min_{\forall k}\left[\min_{\forall i} \Delta d_i(k)\right] \tag{8}$$

$$\Delta d_{\max} = \max_{\forall k}\left[\max_{\forall i} \Delta d_i(k)\right] \tag{9}$$

$\Delta d_{\min}$ and $\Delta d_{\max}$ are the minimum and maximum values of the matrix ΔD respectively, and parameter $\sigma = \Delta d_{\max} - \Delta d_{\min}$. The grey grades used the Euclidean distances (ED) to measure the relationship between the test sequence data and comparative sequences data. The grey grades $f(k)$ are inversely proportional to the distances as

$$\text{ED} = \sqrt{\sum_{i=1}^{n}(\Delta d_i(k))^2} \to ED_{\max}, \quad f(k) \to 0 \tag{10}$$

$$\text{ED} \to ED_{\min}, \quad f(k) \to 1. \tag{11}$$

Recognition coefficient ξ affects the magnitude of grey grades, but does not change the relative relationships between the comparative patterns. For a test sequence A_{test}, we see that $\text{ED}_{\min} \leq \text{ED}(k) \leq \text{ED}_{\max}, \text{ED}_{\min} = \min\{\text{ED}(k)\}$ and $\text{ED}_{\max} = \max\{\text{ED}(k)\}, \forall k = 1, 2, 3, \ldots, K$. The selection of the recognition coefficient depends on the numerical considerations. If the difference between $\text{ED}_{\min}$ and $\text{ED}_{\max}$ is very small, the coefficient ξ is to select $\xi \gg 1$ to make resultant grey relational grades more distinguishable [18]. Recognition coefficient $\xi = 5$ was chosen in this study. If the test vector A_{test} is similar to any comparative vector $A(k)$, the grade $f(k)$ will be a maximum value. Then find the maximum grade, which can be represented as

$$f_{\max} = f(k*) = \max[f(1), f(2), \ldots, f(k), \ldots, f(K)] \tag{12}$$

$$\gamma(k) = \begin{cases} 1, & f(k) = f_{\max} \\ 0, & f(k) \neq f_{\max} \end{cases} \tag{13}$$

where $k*$ is the criterion index in the K comparative sequences; index $\gamma(k) \in [0, 1]$. For m classes classification, the associated class for A_{test} could be expressed as weighting factor $w_{kj} \in [0, 1]$, where m is the total number of possible classes, $j = 1, 2, 3, \ldots, m$. If the test vector A_{test} belongs to class j, the weighted factor w_{kj} equals to one, and the rest factors are zero as Eq. (14). The final grey grade g_j that an unknown vector A_{test} belongs to *Class* j can be represented by Eq. (15)

$$w_{kj} = \begin{cases} 1, & k \in Class\ j \\ 0, & k \notin Class\ j, \end{cases} \quad j = 1, 2, 3, \ldots, m \tag{14}$$

$$g_j = \begin{bmatrix} \gamma(1) & \gamma(2) & \cdots & \gamma(k*) & \cdots & \gamma(K) \end{bmatrix} \cdot \begin{bmatrix} w_{1j} \\ w_{2j} \\ \vdots \\ w_{kj} \\ \vdots \\ w_{Kj} \end{bmatrix} = \sum_{k=1}^{K} \gamma(k) w_{kj}. \tag{15}$$

The dimension of the grey relational vector $\boldsymbol{\Gamma} = [f(1), f(2), f(3), \ldots, f(k), \ldots, f(K)]$ can be reduced from K-dimension to m-dimension ($m = 6$ in our study). These six major classes include the normal beat (Nor), supraventricular ectopic beat (SEB), bundle branch ectopic beat (BBEB), ventricular ectopic beat (VEB), unknown beat (UB), and fusion beat (FB). The outputs are defined as

$$\boldsymbol{G} = [g_{\mathrm{Nor}}, g_{\mathrm{VEB}}, g_{\mathrm{SEB}}, g_{\mathrm{BBEB}}, g_{\mathrm{UB}}, g_{\mathrm{FB}}]. \tag{16}$$

4. Frequency-domain characteristics

4.1. Feature extraction

The QRS complex of the ECG is important information in heart-rate monitoring and cardiac disease diagnosis. Before applying ECG signals, all ECG signals are filtered to produce the baseline corrected ECG signal. The R-waves are detected by a peak detection algorithm, which begins by scanning for local maxima in the absolute value of ECG data. For certain window durations, the searching continues to look for a larger value. If this search finishes without finding a larger maximum, the current maximum is assigned as the R peak [5]. Centered on the detected R peak, the QRS complex portion is extracted by applying a window of 280 ms, and P-wave and T-wave are removed by this window duration. Based on a 360 sampling rate, 100 samples can be acquired around the R peak (Sampling point $P = 100$, 50 points before and 50 points after). After sampling and analogue-to-digital conversion, individual QRS complex is extracted. Then, frequency spectrum of each QRS complex is computed by Eqs. (1) and (2).

The spectrum varies with different cardiac arrhythmias, and power spectra are observed in the frequency range from 1 to 20 Hz. The spectra are plotted and analysed as shown in Fig. 1, and all amplitudes are normalized with maximum amplitude. The amplitudes decrease as the frequency increases, and rapidly vanishes above 12 Hz. Frequency components from 1 to 12 Hz ($n = 12$) are selected for multiple ECG beat recognition. These spectra are not disturbed by high-frequency components above 20 Hz such as power-line interference (50 Hz/60 Hz) and muscle noise, and very low-frequency components (<1 Hz) such as baseline drift and breath [5]. Therefore, power line noise, very low-frequency and high-frequency components are excluded without affecting the frequency-domain features.

4.2. Comparative sequence creation

In this study, the dataset of QRS complexes for six typical heartbeat classes are taken from the MIT–BIH arrhythmias database [12]. The database contains 48 records, and each record is slightly over 30 min long. In most records, the upper signal is a modified limb lead II (ML II) and the lower signal is a modified lead V1 (VI). Six classes have been included in the investigations, involving Nor, VEB, SEB, BBEB, UB, and FB. ¿From these records (ML II Signal), a total of 50 QRS complexes ($K = 50$) are selected including patient numbers 103, 107, 109, 111, 118, 119, 124, 200, 202, 208, 209, 212, 214, 217, 221, 231, 232, and 233, and classified into six types:

– Nor: Normal Beat (•), weighted factors could be encoded as [1 0 0 0 0 0];
– VEB: Premature Ventricular Contraction (V), weighted factors could be encoded as [0 1 0 0 0 0];
– SEB: Atrium Premature Beat (A), weighted factors could be encoded as [0 0 1 0 0 0];
– BBEB: Right and Left Bundle Branch Block Beat (R/L), weighted factors could be encoded as [0 0 0 1 0 0];

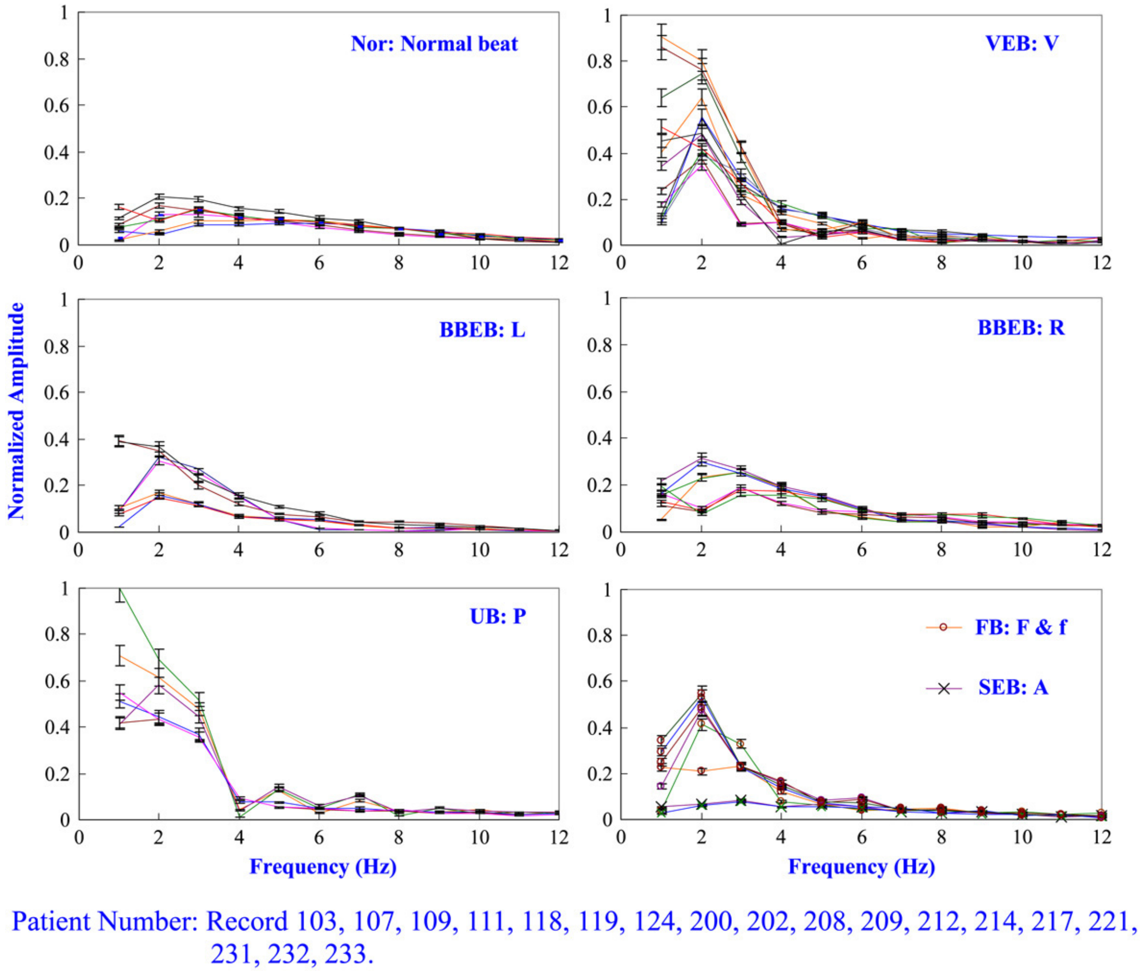

Fig. 1. Power spectra of typical arrhythmia heartbeats in the frequency domain.

– UB: paced beat (P), weighted factors could be encoded as [0 0 0 0 1 0];
– FB: Fusion of Paced/Ventricular and Normal Beat (f/F), weighted factors could be encoded as [0 0 0 0 0 1];

The weighted factors w_{kj}, $k = 1, 2, 3, \ldots, K$, $j = 1, 2, 3, \ldots, m$, are encoded as binary values by Eq. (14) with signal "1" for belonging to *Class* j. FFT are applied to ECG signals for power spectrum estimation to construct various patterns as shown in Fig. 1. The frequency-domain features of six classes are produced for further analysis. To quantify the differences among various classes, the comparative sequences for each class are created as $A(k) = [a_1(k), a_2(k), \ldots, a_i(k), \ldots, a_n(k)]$, $i = 1, 2, 3, \ldots, n$. Frequency-based features will be quantified and used to classify cardiac arrhythmias. The numbers of averaged patterns from the same class are 8-, 13-, 2-, 15-, 6-, and 6-set data respectively. According to the various symptomatic features, we can systematically create comparative sequences with Eq. (4). The dimension of matrix A_{comp} is 50 by 12. The outputs are computed by Eq. (15). The final grade $g_j = 1$ indicates the arrhythmic class.

5. Results and discussion

The proposed diagnostic procedure was developed on a PC Pentium-IV 3.0 GHz with 248 MB RAM, MATLAB workspace, and EXCEL workspace. AAMI recommended practice was used to divide heartbeats into six classes. Based on the MIT–BIH arrhythmias records, single and multiple cardiac arrhythmias are selected for investigation. The performance of the proposed procedure was tested with diagnostic accuracy for unrecorded data. Two study cases are chosen for demonstration, as detailed below.

Table 2
The test results of single cardiac arrhythmia

Record		Number of arrhythmias						CPU time (s)	Accuracy (%)
		Nor	**VEB**	**SEB**	**BBEB**	**UB**	**FB**		
119	Actual	75	25	0	0	0	0	–	–
	Test 1	73	25	0	1	0	1	1.344	98
	Test 2	73	25	0	1	0	1	1.374	98
221	Actual	84	16	0	0	0	0	–	–
	Test 1	82	16	0	1	0	1	1.359	98
	Test 2	82	16	0	1	0	1	1.343	98

Note: (1) Accuracy(%) $= (N_r/N_t) \times 100\%$.
(2) N_r: the number of correctly discriminated beats; N_t: total number of heartbeats.

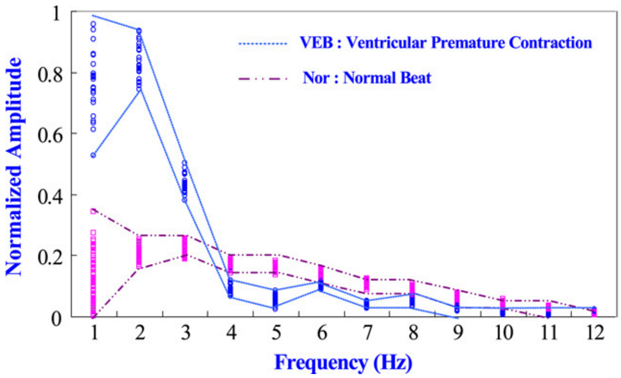

Fig. 2. The frequency spectra of class **Nor** and class **VEB** (patient number: 119).

5.1. Study case 1: Single cardiac arrhythmia

The QRS complexes are extracted within the movable window with each shift in time. P-wave and T-wave can be removed in this window duration. The content of each window is applied to the proposed diagnostic procedure. Using 100 heartbeats (about 1.5 min long) of patient numbers 119 and 221 containing normal beat and premature ventricular contraction, frequency-domain features are computed by FFT algorithm as shown in Fig. 2. Fig. 2 shows the frequency spectra of class Nor and class VEB. In the frequency domain, higher frequency components of VEB are concentrated from 1 Hz to 3 Hz. Class Nor and class VEB occupy different lower and upper amplitudes. For example, amplitude ranges of Nor are $0.00 < a_1 < 0.35$, $0.16 < a_2 < 0.23$, and $0.18 < a_3 < 0.23$, and ranges of VEB are $0.47 < a_1 < 0.95$, $0.74 < a_2 < 0.84$, and $0.38 < a_3 < 0.46$. Different classes appear with their symptomatic patterns in the different amplitude ranges. Because two classes occupy different ranges of amplitudes and frequencies, these features are used in the classification scheme. Table 2 shows the test results. Test 1 shows the results of single cardiac arrhythmia where the overall accuracies are greater than 90%. In ECG measurement, signals may be disturbed by noise such as power-line interference. The ECG signal is sometimes disturbed by power-line interference whose amplitude is approximately 5–6 times less than the R-peak. Test 2 shows the results with presenting ECG signals involving 50 or 60 Hz interference. Because the features are selected from 1 Hz to 12 Hz, high-frequency components are excluded without occupying limited bounds. The diagnostic procedure confirms that the major class is VEB. Overall accuracies are also greater than 90%. Expect a sensitivity of 93% and 89% for class VEB, a specificity of 100% for Nor, and a positive predictivity of more than 80% is obtained to quantify the performance of proposed method with or without a noisy background.

The performance of GRA-based classifier is affected by the width of the grey grade function (Gaussian Function) as Eq. (7). As the width of the function decreases, decision boundaries can become increasingly nonlinear. For variable parameter σ, GRA is capable of approximating arbitrary function for either linear or nonlinear relationships between the input and output. For a narrow Gaussian function, the GRA approaches a nearest-neighbor classifier. Optimal parameter σ can minimize the classification error. In this paper, parameter σ is automatically adjusted by the minimum

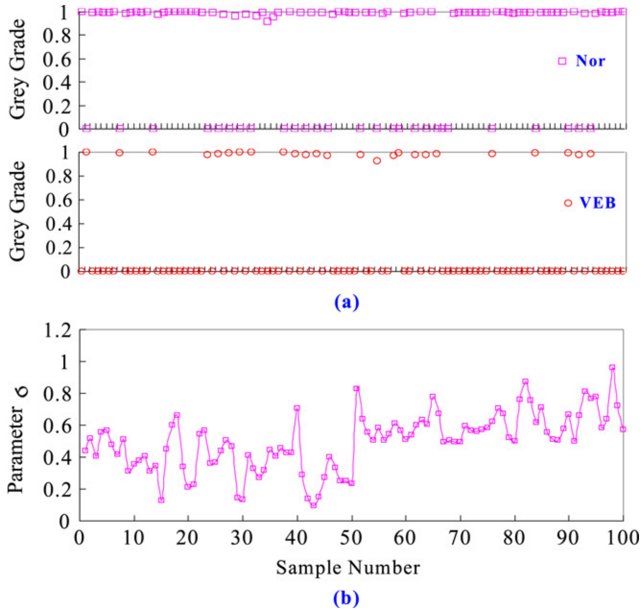

Fig. 3. (a) Grey grades (patient number: 119); (b) Parameter σ variations versus testing samples.

Table 3
The test results of multiple cardiac arrhythmias

Record		Number of arrhythmias						CPU time (s)	Accuracy (%)
		Nor	**VEB**	**SEB**	**BBEB**	**UB**	**FB**		
109	Actual	0	1	0	97	0	2	–	–
	Test 1	0	1	0	95	0	4	1.175	98
	Test 2	0	1	0	95	0	4	1.195	98
208	Actual	61	28	0	0	0	11	–	–
	Test 1	48	26	0	12	0	14	0.975	85
	Test 2	48	26	0	12	0	14	1.189	85
214	Actual	0	4	0	96	0	0	–	–
	Test 1	0	5	0	93	1	1	1.125	97
	Test 2	0	5	0	93	1	1	1.228	97
217	Actual	0	3	0	0	94	3	–	–
	Test 1	0	6	0	4	87	3	1.208	93
	Test 2	0	6	0	4	87	3	1.124	93

and maximum values of the deviation matrix without statistical calculation or the optimum method. The deviation of test sequence and comparative sequences controls the width of grey grade function. The advantage of this function could be applied in the linear and nonlinear model, and a dynamic model could be applied in clinical investigation. With recognition coefficient $\xi = 5$, the grey grades indicate the normal and abnormal and confirm that the grey grades are between 0.0 and 1.0. Fig. 3(a) shows the grey grades of patient number 119 and there appears to be two classes, Nor and VEB. If the test sequence is similar to any comparative sequence, the grey grade will be a maximum value and close to one. Fig. 3(b) shows the parameter σ variations versus testing samples with one hundred heartbeats. The proposed method can recognize the heartbeats with a high degree of confidence.

5.2. *Study case 2: Multiple cardiac arrhythmias*

Some of the clinical diagnostic cases include multiple cardiac arrhythmias; for instance, ventricular ectopic beat, bundle branch ectopic beat, fusion beats and paced beats. One hundred heartbeats of patient numbers 109, 208, 214 and 217 containing multiple cardiac arrhythmias [13] were used. Table 3 shows the test results. The results of Test 1

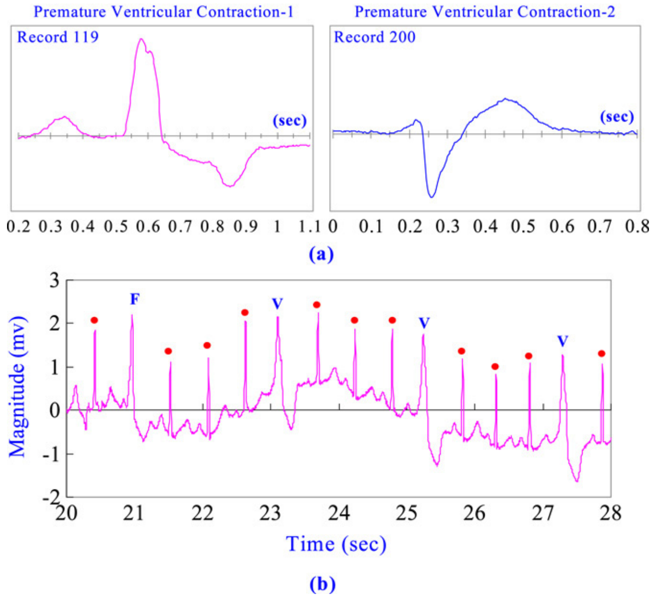

Fig. 4. (a) Typical PVC beats (patient number: 119 & 200); (b) ECG signals with artifact noises (patient number: 208, ML II signal).

confirm that the major classes are BBEB, VEB, FB, and UB. The diagnostic processes recognized 97 and 96 BBEBs with two and three failures in patient numbers 109 and 214 respectively, 28 VEBs and 11 FBs with two and three failures in patient number 208, and 94 UBs with seven failures in patient number 217. Test 2 also shows the results of multiple abnormal beats involving noisy interference. The overall accuracies are also greater than 85%. The GRA-based classifier does not promise results with 100% accuracy due to the morphology variations of ECG waveforms being different for different patients, even for the same patient or for the same type such as premature ventricular contraction (PVC) beats, and ECG signals with artifact noises and serious baseline wander as shown in Fig. 4. For example, Table 3 shows the detection results of patient number 208 where there are thirteen misclassification errors of class Nor due to artifact noises and baseline wander. All ECG signals must be preprocessed with a median filter to remove unwanted noises and to correct the baseline [3]. The PVC heartbeats are multiform heartbeats including ventricular bigeminy (B) and ventricular tachycardia (VT). The inclusion of the abnormal beats without using them in the comparative sequences will affect the efficiency of the proposed method. With this procedure, the preprocessing stage and the adding of special features to the current database could enhance the diagnostic confidence in discriminating abnormal heartbeats.

5.3. *Performances comparison*

Table 4 compares the performances of the proposed method, fuzzy logic and novel ANN. The fuzzy logic approach needs to determine the linguistic variables, membership functions with "low", "medium", "high", "rather", and "roughly" describing amplitude ranges of each frequency spectrum and inference rule base. The fuzzy logic has six input variables (Frequency spectra from 1 Hz to 6 Hz) with 21 membership functions, one output variable with six membership functions and 66 inference rules. Inference results are obtained by the centre of gravity defuzzifier, mean of maxima defuzzifier, etc. The inference rules and defuzzifier must be continuously revised according to the patients' condition. Conventional ANN's network weights and learning rates were determined by the tedious and trial-and-error procedure necessitating the iteration process for updating weights, and the need to determine the network architecture such as the number of hidden layers and hidden nodes, which is difficult to retrain with new training data. Novel ANNs have been presented to improve these drawbacks such as the learning stage without any iteration for updating weights. However, the performance is affected by the parameters of hidden activation function. The choice of parameters will affect the estimation error, and the suitable ranges are determined experimentally [19]. Refining the parameter can enhance the detection accuracy by using the optimum method [20], but the learning process requires iterative training without a guaranteed global minimum. The proposed method employs a straightforward mathematical operation to

Table 4
Comparison of the proposed method with the Fuzzy logic and Novel ANN

Task	Method		Proposed method
	Fuzzy logic	Novel ANN	
Membership function	Y	N	N
Inference rule base	Y	N	N
Database	N	Y	Y
Training data	N	Y	N
Training iteration	N	Y	N
Training time	N	Fast	N
Parameter tuning	N	Experience	N
Result inference	Defuzzifier	Sorting	Sorting
Adaptation capability	Moderate	Good	Good
Detection precision	Moderate	High	High

Note: Y: Yes, N: No.

process numerical computation for numerical data or binary data, expandable or reducible comparative sequences without adjusting any parameter. If clinicians provide some suggestion or new features are produced in clinical investigation, comparative sequences and weighting factors can keep on growing by adding new data to the database. The database can be enhanced with each new sample added to the current active database. Table 4 shows that the outcomes of the proposed method are superior to other AI approaches.

6. Conclusion

The diagnostic procedure based on novel GRA is presented to recognize cardiac arrhythmias. The FFT technique is used to estimate the frequency-domain features. Different classes occupy different ranges of amplitudes and frequencies. Frequency components from 1 Hz to 12 Hz are selected for multiple ECG beat recognition. GRA-based classifier then uses these features to identify the cardiac arrhythmias. For both recorded and unrecorded data, the experimental results demonstrate the efficiency of the proposed method. The proposed method can also work in a dynamic environment with continuity add-in or delete-off features without adjusting parameters and avoiding the determination of the linguistic variables, membership functions, inference rules, network architecture, and parameters assignment. Compared with other AI approaches, the proposed method shows good performance in detection. Designing a virtual medical instrument, measurement, data storage, signal processing, signal classification, decision support and human computer interface have become aided functions for disease diagnosis. The proposed diagnostic algorithm is easy to implement in the PC-based virtual instrument. MATLAB–Excel Link is a software add-on to integrate the Excel and window-based MATLAB computing environment. Excel Link provides data management including create, append, overwrite, or delete with data from the Excel workspace and the computing command from MATLAB workspace. The proposed method can be further used as a tool to help in ECG, beats recognition and can be integrated into the monitoring device.

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