Detection of life-threatening cardiac arrhythmias using the wavelet transformation

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Abstract—*Time-frequency wavelet theory is used for the detection of life threatening electrocardiography (ECG) arrhythmias. This is achieved through the use of the raised cosine wavelet transform (RCWT). The RCWT is found to be useful in differentiating between ventricular fibrillation, ventricular tachycardia and atrial fibrillation. Ventricular fibrillation is characterised by continuous bands in the range of 2–10 Hz; ventricular tachycardia is characterised by two distinct bands: the first band in the range of 2–5 Hz and the second in the range of 6–8 Hz; and atrial fibrillation is determined by a low frequency band in the range of 0–5 Hz. A classification algorithm is developed to classify ECG records on the basis of the computation of three parameters defined in the time–frequency plane of the wavelet transform. Furthermore, the advantage of localising and separating ECG signals from high as well as intermediate frequencies is demonstrated. The above capabilities of the wavelet technique are supported by results obtained from ECG signals obtained from normal and abnormal subjects.*

Keywords—*Electrocardiography, Ventricular fibrillation, Ventricular tachycardia, Wavelet transformation*

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1 Introduction

THERE ARE a number of cardiac arrhythmias that could be catastrophic and life threatening. Among these are ventricular fibrillation (VF), ventricular tachycardia (VT) and atrial fibrillation (AF). VF is considered to be the most life threatening because the heart fails to pump blood effectively, and the patient could die within minutes unless normal heart rhythm is restored using an electrical defibrillator.

The reliable detection and diagnosis of this arrhythmia constitute a challenge, not only in the monitoring of patients in CCU, but also in the design of automatic implantable defibrillators where the electric shock is automatically initiated by the detection of these episodes (LANGER *et al.*, 1976; HERBSCHLEB *et al.*, 1980; MIROWSKY *et al.*, 1981; MOWER *et al.*, 1983).

The accuracy of VF detection is of extreme importance because failure in detection or false identification is fatal (CLAYTON *et al.*, 1993). The detection of VF is difficult because the ECG has a waveform that is different from other abnormal rhythm waveforms (BARRO *et al.*, 1989). Furthermore, practical problems such as poor electrode contact can produce artefacts that mimic these rhythms (CLAYTON *et al.*, 1993).

Several research groups have been working on the above problem, and a number of detection and analysis techniques have been used (NYGARDS and HULTING, 1977; MEIJ and ZEELENBERG, 1987; BARRO *et al.*, 1989; CHALLIS and KITNEY, 1990; THAKOR *et al.*, 1990; CLAYTON *et al.*, 1991). These include, in general, either time-domain or frequency domain analysis techniques.

In time domain analysis, threshold crossing intervals (TCI) (HERBSCHLEB *et al.*, 1979; THAKOR *et al.*, 1990) and autocorrelation (ACF) methods are used (AUBERT *et al.*, 1982; CHEN *et al.*, 1987). TCI was used to detect VF and was characterised by a mean of 105ms that corresponds to a dominant frequency of 9.5 Hz, whereas for TCI = 220 ms corresponds to a dominant frequency of 4.5 Hz for the detection of VT (THAKOR *et al.*, 1990). Other research groups have different values (HERBSCHLEB *et al.*, 1979; AUBERT *et al.*, 1982). The short-time ACF was used to distinguish between VF and other rhythms, depending on the fact that VF is a periodic signal (AUBERT *et al.*, 1982; CHEN *et al.*, 1987, CHALLIS and KITNEY, 1990).

In the frequency domain technique, the VF-filter (KUO and DILLMAN, 1978; MEIJ and ZEELENBERG, 1987) as well as spectral analysis techniques were used (CLAYTON *et al.*, 1991). The VF-filter method relies on approximating the VF signal as a sinusoidal waveform. The method is equivalent to using a bandpass filter, the central frequency of which is the mean signal frequency. The spectral analysis technique relies on the fact that the VF frequency contents are concentrated in the bandwidth 4–7 Hz (CLAYTON *et al*, 1991). The increased power in this band of frequencies is the major indication of the presence of VF.

The above spectral analysis technique is applied to stationary signals. However, abrupt changes in the non-stationary ECG signal are spread over the whole frequency range.

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Important time-varying statistical characteristics are lost once the signal has been Fourier transformed. In recent years time-frequency analysis techniques have proved to be useful in experimental and clinical cardiology. These include the detection of ECG late potentials (MESTE *et al.*, 1991; DICKHAUS *et al.*, 1994) and high resolution electrocardiography in general (MORLET *et al.*, 1991).

In this paper, the wavelet theory is used as a time-frequency representation technique to provide a method for enhancing the detection of life threatening arrhythmias.

2 Wavelet transform

The wavelet transform makes it possible to detect small, transient signals, even if they are hidden in large waves (GROSSMANN *et al.*, 1987; KRONALD *et al.*, 1987; GROSSMAN and KRONALD, 1988; RIOUL and VETTERLI, 1991, SHENSA, 1992, CAIRE *et al.*, 1993). This technique shows advantages over the short time Fourier transform because of the poor frequency resolution inherent in the use of short segments. The wavelet transform $WT(t,f)$ is defined as:

$$WT(t,t) = \sqrt{\frac{1}{a}}\int_{\tau} S(\tau)g^{*}\left(\frac{1}{a}(\tau - t)\right)d\tau \tag{1}$$

where $S(t)$ is the signal, $g(t)$ is the analysing wavelet, and a is the dilation /contraction parameter defined as f_o/f.

The basis functions are obtained from a given analysing wavelet $g(t)$ by dilation or contraction and by time shifts. The analysing wavelet $g(t)$ should satisfy a certain number of properties. The most important are integrability, square integrability and that it has no DC-component (RIOUL *et al.*, 1991; HLAWATSCH and BOUDREAUX-BARTELS, 1992). Moreover, it is convenient to assume that $G(\omega) = 0$ for negative frequencies. A frequently used analysing wavelet is the modulated Gaussian function that was introduced by Morlet and Grossman (GABOR, 1946).

$$g(t) = \exp\left(-\frac{t^2}{2} + j\omega_o t\right) \tag{2}$$

Admissibility conditions are satisfied with ω_o between 5.0 and 6.0 (GOUPILLAND *et al.*, 1984; GROSSMANN *et al.*, 1987). Another analysing wavelet is the raised cosine, which is defined as

$$g_{\beta,\sigma}(t) = \frac{\frac{\beta}{\pi}\sin\left(\frac{\beta}{\pi}t\right)\cos(\sigma t)e^{j\beta t}}{1 - \left(\frac{2\sigma t}{\pi}\right)^2} \tag{3}$$

where β denotes the bandwidth of the filter, and σ signifies the roll-off frequency.

The importance of this analysing wavelet is that the signal is analysed through an orthogonal wavelet so that the time and spectral detection of the signal are enhanced. Also, this wavelet has the ability to reduce the redundancy and interference in the WT without sacrificing accuracy (PEEBLES, 1976; 1987).

The wavelet transform as defined by eqn. 1 is linear. Although the linearity is a desirable property, it is desirable to deal with a quadratic structure of the wavelet transform when we want to interpret the wavelet as a time-frequency energy distribution. The scalogram is defined as the squared magnitude of the wavelet transform and it can be interpreted in terms of the signal energy.

3 Methods

3.1 *Wavelet analysis*

The algorithms presented above were tested using Matlab software package version (4) running on a PC with an 80486 processor. The readings were based on lead II and sampled at 512 samples per second. The analysing frequency ranged from 0.05–100 Hz. This analysis was performed on 2 s of subject data under consideration. The computation of the wavelet transform is performed by calling FFT three times for a given value of the scaling parameter a. The determination of the spectral zones and the feature extraction are carried out based upon the scalogram. Fig. 1 shows the flow chart of the signal-processing techniques that describes the way in which the data have been processed.

3.2 *ECG data*

Performance evaluation was conducted using the MIT-DB and the ECG database at the Electronic Engineering Department of Yarmouk University (YUDB). This data base was developed in cooperation with Kent University in the UK, and it consists of Holter ECG recordings obtained from different patients. In this initial study, a total of 45 ECG records (8 with predominant rhythm, 12 associated with ventricular fibrillation, 13 with ventricular tachycardia and 12 with atrial fibrillation) were studied.

3.3 *ECG analysis*

To quantify the differences between the various groups with the help of the wavelet transform, we compared the densities for different frequency bands. That is, we computed the volume underneath the 3D plots of the square modulus of the wavelet transform for several regions of the time–frequency plane. The volume can be interpreted as the energy of the signal within that particular time–frequency region. We divided the time–frequency plane into seven bands ranging from 0 to 15 Hz. For sinus rhythm the energy parameter was calculated within the time intervals T_1 and T_2 integrated over the whole frequency axis. The time interval T_1 was determined by the region of the QRS-complex, and the time interval T_2 was determined by the region of the T-wave (see for example LAGUNA *et. al.*, (1996) and MUKHOPADHYAY and SIRCAR (1996).

As the wavelet transform is very sensitive to abrupt changes in the time direction, the energy parameter over the given time intervals attains relatively large values for normal subjects. We refer to this parameter as T_v and define it as the sum of the energy parameters computed within the intervals T_1 and T_2. Although the signals of AF and VT exhibit a QRS-complex, the parameter value T_2 for these signals remains relatively small, owing to the absence of abrupt changes in the region of the T-wave. Therefore the value of T_v will still be smaller than that for the normal subjects.

The discrimination between different kinds of arrhythmia was carried out by calculating the energy parameters over frequency bands. As shown in Table 1, the AF is concentrated in the range 0–5 Hz. To discriminate AF from other arrhythmias we compared the value of the energy parameter in the frequency band 0–2 Hz with a threshold value, and referred to this value as A_1. If A_1 was >0.2, the case was identified as an AF group. If it was not an AF group, it could be either a VT or VF case.

The classification of the VT and VF groups was then carried out by computing the value of the energy parameter over the frequency band 2–10 Hz; we called this parameter A_2. The VF group was identified by a threshold value $A_2 > 0.7$, whereas V_T

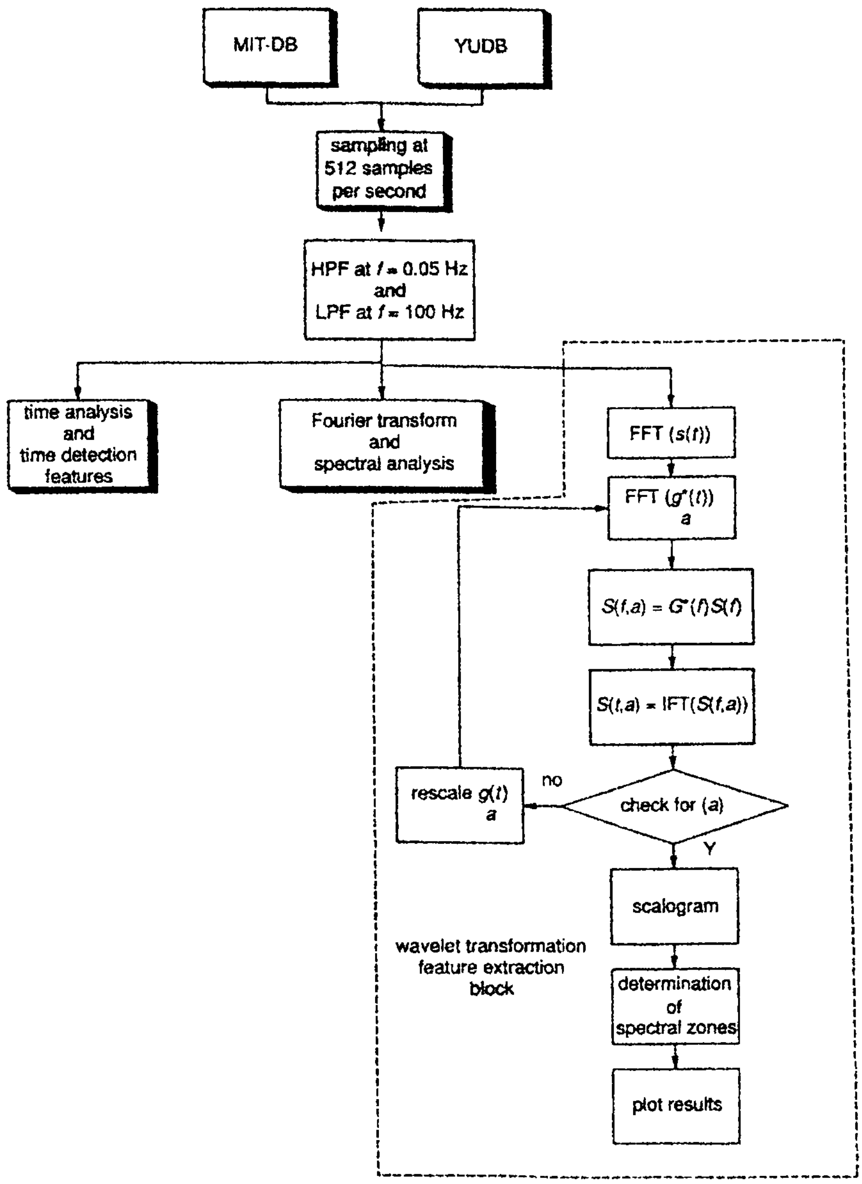

Fig. 1 *Flowchart representing the way by which the data has been processed*

Table 1 *Scalogram results obtained from some arrhythmia signals for different frequency bands.*

Arrhythmia files		0–2 Hz	2–5 Hz	5–6 Hz	6–8 Hz	8–10 Hz	10–12 Hz	12–15 Hz
AF Files	p203 MIT-DB	0.2982	0.2688	0.0706	0.1204	0.0910	0.0856	0.0653
	p222 MIT-DB	0.2927	0.2286	0.0555	0.1135	0.1014	0.1115	0.0968
	p10 YUDB	0.2173	0.2167	0.0669	0.1362	0.1190	0.1330	0.1109
VT files	p106 MIT-DB	0.1478	0.3003	0.0889	0.1549	0.1149	0.1040	0.0893
	p200 MIT-DB	0.1488	0.3336	0.0886	0.1371	0.1072	0.1009	0.0838
	p203 MIT-DB	0.1394	0.3040	0.0917	0.1539	0.1177	0.1117	0.0816
	p205 MIT-DB	0.0481	0.2461	0.0935	0.1720	0.1390	0.1591	0.1422
	p20 YUDB	0.0224	0.3869	0.1276	0.1900	0.1002	0.0952	0.0778
VF Files	p207 MIT-DB	0.1015	0.4007	0.1136	0.1590	0.0933	0.0772	0.0546
	p207 MIT-DB	0.0460	0.3742	0.1207	0.1945	0.1143	0.0837	0.0666
	p207 MIT-DB	0.0933	0.3962	0.1233	0.1790	0.0893	0.0694	0.0495
	p207 MIT-DB	0.0640	0.3519	0.1312	0.2255	0.1318	0.0655	0.0301
	p30 YUDB	0.0835	0.1927	0.1044	0.1881	0.1603	0.1627	0.1084

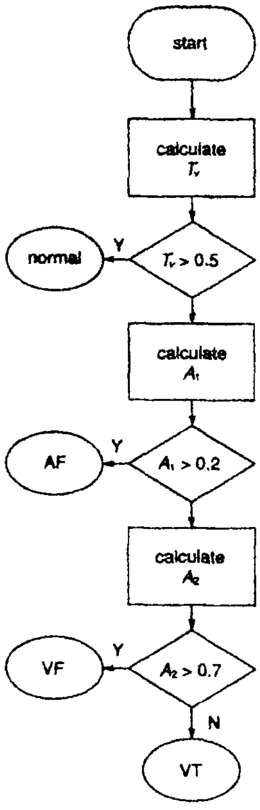

Fig. 2 *Flowshart showing the principle of the classification scheme*

group was identified by $A_2 < 0.7$. This classification scheme is illustrated in Fig. 2 as a flowchart.

4 Results and discussion

4.1 *Analysis examples*

Fig. 3 shows the results obtained from the simulated test signal. It shows respectively, the test signal, the spectrum of the signal, the magnitude contour of the RCWT and the 3D plot of the RCWT. The test signal $s(t)$ is composed of a sinusoidal signal at 6 Hz. The test signal also has a very small distortion at $t = 0.6$, denoted by δ_1, where δ_1 is an impulse of amplitude 0.5% of the signal peak value. This small distortion was added in order to illustrate the time detection capabilities of the RCWT and the frequency resolution at low frequency due to δ_1 contribution. The 3D surface plot shows a peak at 6 Hz and a roll off in the frequency range 3–9 Hz resulting from the existence of the delta irregularity (HLWATSCH and BOUDREAUX-BARTELS, 1992).

Fig. 4 shows nearly two cycles of a normal sinus rhythm ECG. It has a regular and normal QRS shape QRS with heart rate of 62 beats $\min^{-1}$. The spectrum of the signal is located in the range of 0.1–30 Hz. The magnitude contour of the RCWT shows the variation of the signal in the time-frequency domain. The power is located within the QRS complexes and concentrated in a frequency range of 4–10 Hz. The T-wave appears near the QRS complex with low frequency content concentrated in the range of 1.5–5 Hz.

Fig. 5 shows the ECG signal obtained from a patient with atrial fibrillation. It consists of a single QRS-complex. The T-wave is not distinguishable. The average heart rate for this patient is 62 beats $\min^{-1}$. The QRS is regular with normal shape. The spectrum of the signal is located in the range of 0–30 Hz. The RCWT is characterised by a dominant low frequency signal. This signal extends to cover the whole time domain and a frequency band of 0–5 Hz. Also, the wavelet contour separates these low-frequency signal frequency contents from those of noise that have been localised in the range of 5–17 Hz.

Fig. 6 shows the results obtained from a patient with an episode of ventricular tachycardia. The signal shows regular QRS-complexes. The heart rate is 300 beats $\min^{-1}$. The spectrum of the signal is in the range of 2–10 Hz, manifested as bands of frequencies centred around 3, 7 and 9 Hz. The RCWT contour shows that the signal has two major frequency bands, centred at 3 and 7 Hz that cover the whole time domain.

Fig. 7 shows results obtained from a patient with ventricular fibrillation. The VF signal has a random shape with unrecognisable ECG features. The related signal features cannot be detected, either in time- or in frequency-domain analysis techniques. In the frequency domain, the signal contents are centred in the band 1–8 Hz. The RCWT is intended to show more informative results than time or frequency techniques. As shown, the RCWT contour separates the detection of

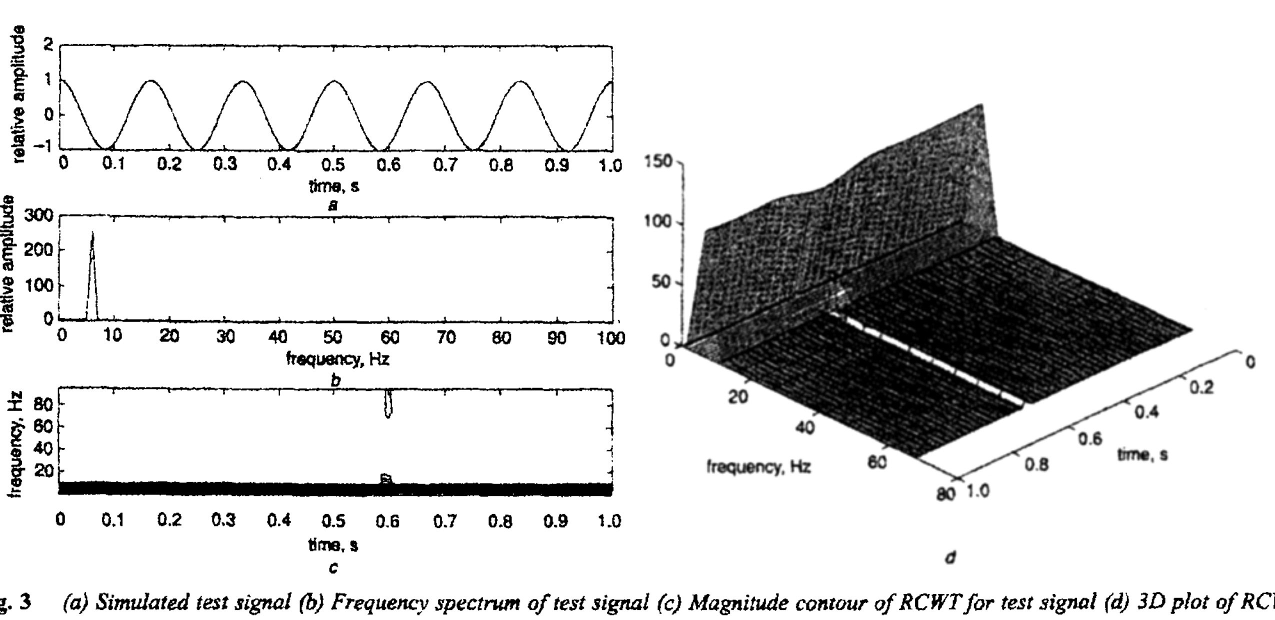

Fig. 3 *(a) Simulated test signal (b) Frequency spectrum of test signal (c) Magnitude contour of RCWT for test signal (d) 3D plot of RCWT*

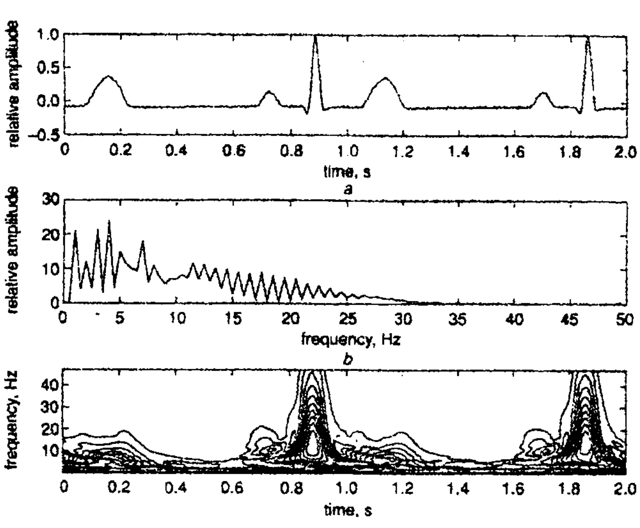

Fig. 4 *(a) Normal ECG signal. (b) Frequency spectrum of normal ECG signa. (c) Magnitude contour of RCWT for normal ECG signal*

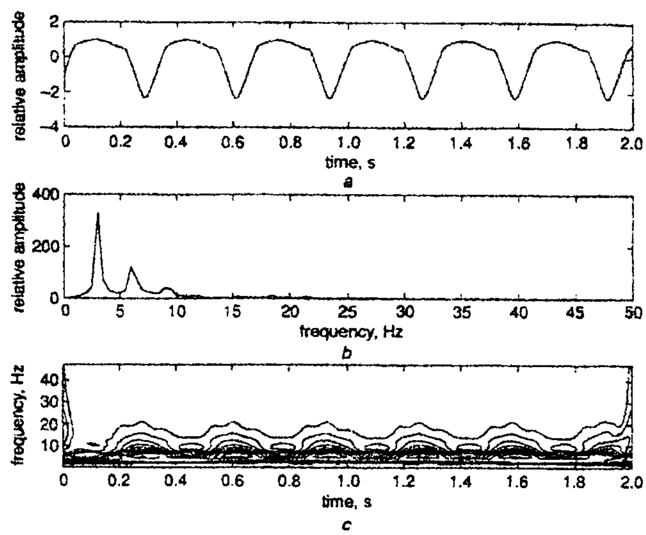

Fig. 6 *(a) ECG signal obtained from patient suffering from ventricular tachcardia. (b) Frequency spectrum of ECG signal. (c) Magnitude contour of RCWT for ECG signal*

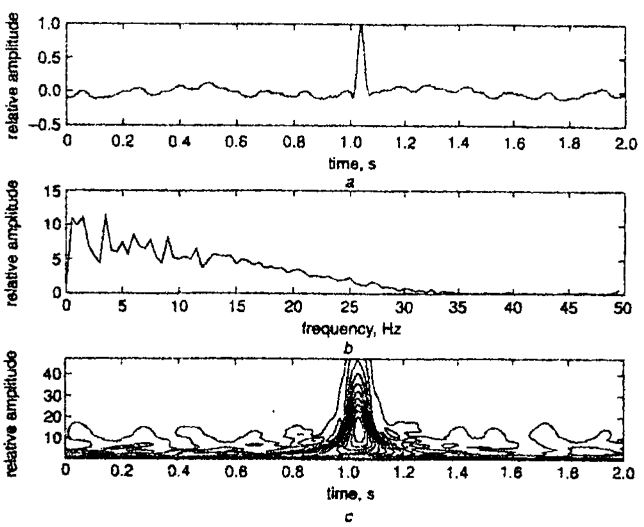

Fig. 5 *(a) ECG signal obtained from patient suffering from atrial fibrillation. (b) Frequency spectrum of ECG signal. (c) Magnitude contour of RCWT for ECG signal*

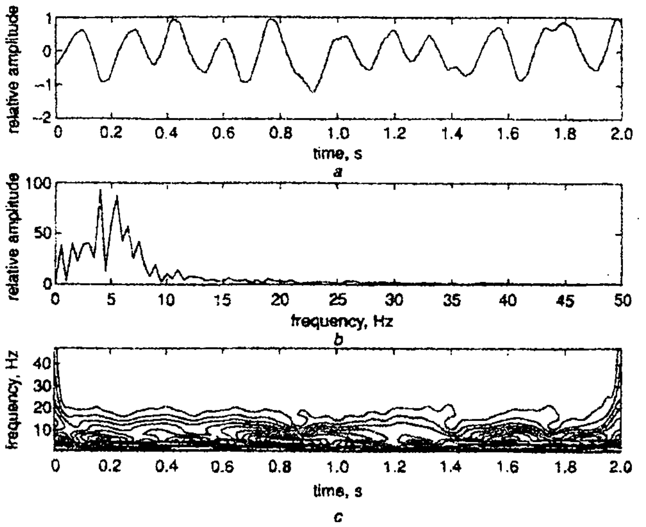

Fig. 7 *(a) ECG signal obtained from patient suffering from ventricular fibrillation. (b) Frequency spectrum of ECG signal. (c) Magnitude contour of RCWT for ECG signal*

ventricular fibrillation from that of ventricular tachycardia, as VF has a broad band of frequencies in the range of 2–10 Hz and extends over the whole time domain. This feature distinguishes VF from normal ECG, VT and AF. Furthermore, the ability of the wavelet transform to separate noise parameters from signal parameters at different time instants is clarified.

Another example for VF, which was obtained from the MIT ECG database, is shown in Fig. 8. Again, the RCWT contour shows a broad band of frequencies, in the range of 2–9 Hz, that extend over the whole time domain.

4.2 *Comparison between ECG groups*

Table 1 shows the distribution of energy with respect to these frequency bands for different arrhythmia files. For AF, the energy is concentrated in the range 0–5 Hz, the VT case shows two apparent frequency bands in the range of 2–5 and 6–8 Hz, and the VF has a broad frequency band in the range 2–10 Hz. As is demonstrated in the Table, a clear distinction between the various frequency components is achieved using the energy parameter defined by the wavelet transform. Based upon the energy parameters, we were able to deduce a simple set of rules to construct an operational classification scheme by comparing these parameters with a set of thresholds.

Table 2 summarises the results of this classification scheme. With these results we can determine the sensitivity and the specificity of the algorithm. We show these results in Table 3. We should like to point out the fact that the type of database will influence the threshold values slightly. We could have obtained better specificity and sensitivity values if we had used slightly different threshold values for the MIT-DB and YUDB.

The suggested energy parameter for discrimination is only a first attempt in describing such patterns. In spite of the fact that these quantification results are obtained from the learning

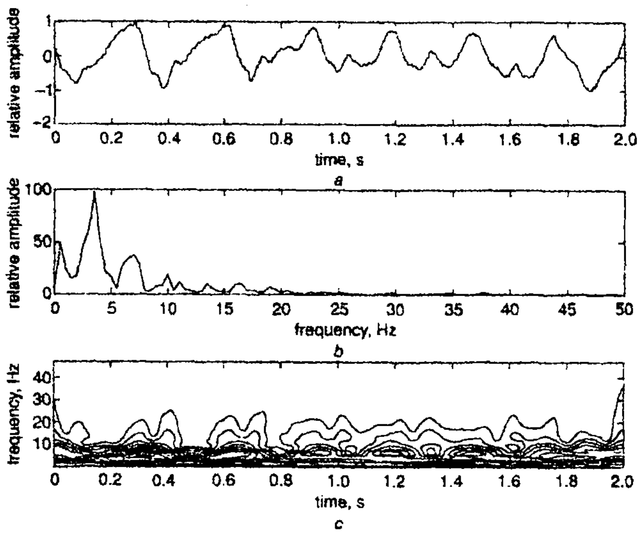

Fig. 8 *(a) ECG signal obtained from MIT-DB for patient suffering from ventricular fibrillation. (b) Frequency spectrum of ECG signal. (c) Magnitude contour of RCWT for ECG signal*

Table 2 Classification according to energy parameter in time-frequency plane of wavelet transform

	Detected arrhythmia				Total
Actual arrhythmia	VF	VT	AF	NR	45
VF	11	2	0	0	13
VT	1	11	0	0	12
AF	0	0	11	1	12
NR	0	0	1	7	8

Table 3 Sensitivity and specificity for learning set groups

	FP	FN	Sensitivity, %	Specificity, %
VF	2	1	91.7	83.3
VT	1	2	84.6	92.3
AF	1	1	91.7	91.7
NR	1	1	87.5	87.5

FP = false positive; FN = false negative

set, and thus optimistically biased, we believe that the results are promising and confirm the importance of this approach.

5 Conclusions

In this paper, the RCWT is implemented and tested on normal as well as life-threatening arrhythmias such as AF, VT and VF. The RCWT revealed more information regarding the frequency contents of the P-, QRS- and T-waves against time. The RCWT also revealed some interesting characteristic features such as low frequency band (0–5 Hz) for AF, two distinct frequency bands (2–5 and 6–8 Hz) for VT, and a broad frequency band (2–10 Hz) for VF. The classification scheme that has been derived from the scalogram of the wavelet transform has proved to be simple and useful in differentiating between different types of arrhythmia. Owing to the small number of available life threatening arrhythmia signals, future work will concentrate on obtaining more of these signals and conducting further experiments using the RCWT. Furthermore, future work will concentrate on developing software for automatic detection of life threatening arrhythmias using the wavelet transformation.

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