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Ventricular late potential analysis with musical and harmonic wavelets

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Abstract

Harmonic and musical wavelets were introduced by DE Newland in 1994, and have their spectrum tightly defined, therefore greatly reducing spectral leakage that may disturb signal frequency analysis. We have explored the ability of these wavelets to perform detection and quantification of ventricular late potentials (VLP) through our multiresolution time-scale method of energy comparison between the ST and TP segments of the ECG. Since reduction of spectral leakage improves the method's reliability, Newland wavelets provided better results than Daubechies wavelets in our study cases. The only drawback is the comparatively reduced time resolution of Newland wavelets. This required us to concatenate a number of ST segments to form a longer data set that is more representative of the high-resolution ECG (HR-ECG) of a patient than one individual beat. This approach may also be considered for other applications in the HR-ECG field. The spectral properties of the Newland wavelets play a major role in the improvement in our results. © 1999 IPEM. Published by Elsevier Science Ltd. All rights reserved.

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1. Introduction

Ventricular late potentials (VLP) are cardiac microvolt signals arising from the delayed inhomogeneous propagation of the depolarisation wave through ventricular tissue. They have diagnostic value as predictors of malignant arrhythmias and cardiac arrest. Traditional time analysis methods excessively depend on the noise level and the location of the QRS limits [1,2]. Time–frequency methods are a promising modern alternative still under scrutiny, for which the spectrogram [3] and the Wigner–Ville methods have mainly been used [4]. The spectrogram's limitations are the low resolution and dependence on the window type, while the Wigner–Ville Transform exhibits cross terms. Wavelets are one of the most recent tools adopted for high-resolution ECG (HR-ECG) research. Reports have pointed out the superior ability to discriminate low energy transients such as VLPs [4,5]. We present a quantitative method based on harmonic and musical wavelets [6–8]. Our HR-ECG acquisition set-up had the following parameters: ADC effective resolution, 12 bits; group delay error, 0.77%; noise level below 1 μV; final stage sampling frequency, 2.2 kHz; and bandwidth, 550 Hz.

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2. Discrete Wavelet Transform (DWT) with harmonic and musical wavelets

Newland wavelets are given by Newland [8]:

$$w_{m,n}\left(x-\frac{k}{n-m}\right)= \frac{\exp\left(in2\pi\left(x-\frac{k}{n-m}\right)\right)-\exp\left(im2\pi\left(x-\frac{k}{n-m}\right)\right)}{i2\pi(n-m)\left(x-\frac{k}{n-m}\right)} \quad (1)$$

For $m = 2^j$ and $n = 2^{j+1}$ the harmonic wavelet family

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is obtained, in which case it makes more sense to use the terminology term *level* (m,n) instead of wavelet *level* j. Wavelets will be translated by steps $k/(m - n)$ where k must be a constant. Unlike the Daubechies wavelets [9], these have their spectrum tightly confined, thus drastically reducing *spectral leakage*, although with the sacrifice of time resolution by a factor of two. For $m = 2^{r/12}$ and $n = 2^{(r+1)/12}$, r being a real integer, the musical wavelet family is obtained, for which each octave is divided into 12 steps as in the musical scale. The frequency resolution is greatly increased with corresponding reduction of time resolution. For instance, a real signal sequence with 2048 samples would have 512 samples in the higher resolution level of the scalogram. This 1/4 resolution reduction is explained as follows: one half is due to the half of the transform being the complex conjugate of the other half, therefore conveying no new information; the other half is due to the way the scalogram is obtained where the coefficients of the last decade correspond to the higher resolution and the others group behind these. The transform is obtained through the Newland 'sandwich' algorithm [6], comparable in efficiency to the Mallat tree algorithm [10]. The multiresolution signal at a certain frequency level is obtained by performing the Inverse Discrete Wavelet Transform with the coefficients pertaining to that level only.

3. VLP quantification and multiresolution scheme

Time–frequency analysis has been applied to VLP quantification. Haberl et al. [11] proposed a figure, the factor of normality (*FN*), obtained by a correlation process in the frequency domain between the Fourier spectrum of each time slice of the ST segment with the average spectrum of the last portions of the ST segment (where no VLPs are supposed to be present) or the TP segment. A correlation coefficient is obtained that, by area comparison, produces the *FN* figure which quantitatively accounts for the presence of VLP. Other authors have used the same procedure with the Wigner–Ville Transform instead of the Fourier Transform [12]. Theoretically, a person without VLP would have $FN = 0\%$. Unfortunately, in practical situations this is normally not so. Values as high as 40% have been considered normal. Thresholds vary substantially between research groups that use the same method, and have sometimes been established empirically based on clinical experience. Ultimately, the key factors in this variation are the sensitivity and noise level of the acquisition set-up. A variety of acquisition systems is in use. It is quite possible that for a patient undergoing the same VLP test methodology (say the spectrogram) in two facilities, the results could vary to such an extent that different diagnosis and consequent treatment could follow.

In this work we introduce a VLP quantification methodology based on the concatenation of a number of successive ST segments, typically 10–20, to build a longer data set necessary to overcome the low time resolution of musical wavelets [12–14]. Concatenation continues until 2048 samples are available at a sampling frequency of 2.2 kHz. We observe that this signal may more accurately relate the HR-ECG to the patient's condition, rather than one individual beat or the averaged signal.

To perform the multiresolution analysis scheme explained below, concatenation was also applied to the TP segment. The edges of the concatenated signals may introduce new high frequency spectral components that are artefacts. Since the ST segments are, at the microvolt level, somewhat concave we have inverted the polarity of every second segment, therefore obtaining a low frequency sine-wave-like baseline, easily retained in the low scales of the wavelet transform. This signal is shown in the upper part of Fig. 1. Polarity inversion also greatly reduces the slope arising from the concatenation process. The lower plot in Fig. 1 represents the same procedure for the TP segment for which no polarity inversion was performed, since each individual TP segment is a smoother signal. The generated slope was digitally removed, a simple detrending operation consisting of subtracting a best straight-line fit of the data.

Our multiresolution scheme is based on the energy comparison between the ST (or concatenated ST) and the TP (or concatenated TP) segments of the ECG. Hereafter we will use these terms interchangeably. The TP segment is used as a reference since increased energy in the ST segment is interpreted as indicating the presence of VLP. The energy of the VLP themselves is as low as 1% of the overall energy of the ST segment when they are present. Signal DC and low frequency components such as the typical ST slopes contain most of the ST energy.

Using wavelets, we are able to observe the signal at different resolutions, discarding the low frequency scales where most of the unwanted energy lies. Fig. 2 shows the method applied to one beat of a patient seven days after myocardial infarction. The left column relates to the TP segment only, which is shown at the top with 6.396 μV (RMS_{total}). Most of the energy content of the TP segment is 50 Hz interference and this is quite visible. We allowed this interference level for testing purposes, although we could easily reduce it drastically in the hardware. All the signals below this are the result of the harmonic wavelet decomposition of the TP signal. The frequency bands and the *RMS* values are shown above the individual plots. The following relation holds:

$$RMS_{\text{total}} = \sqrt{\sum_i (RMS)_i} \tag{2}$$

where $(RMS)_i$ is referred to each multiresolution signal.

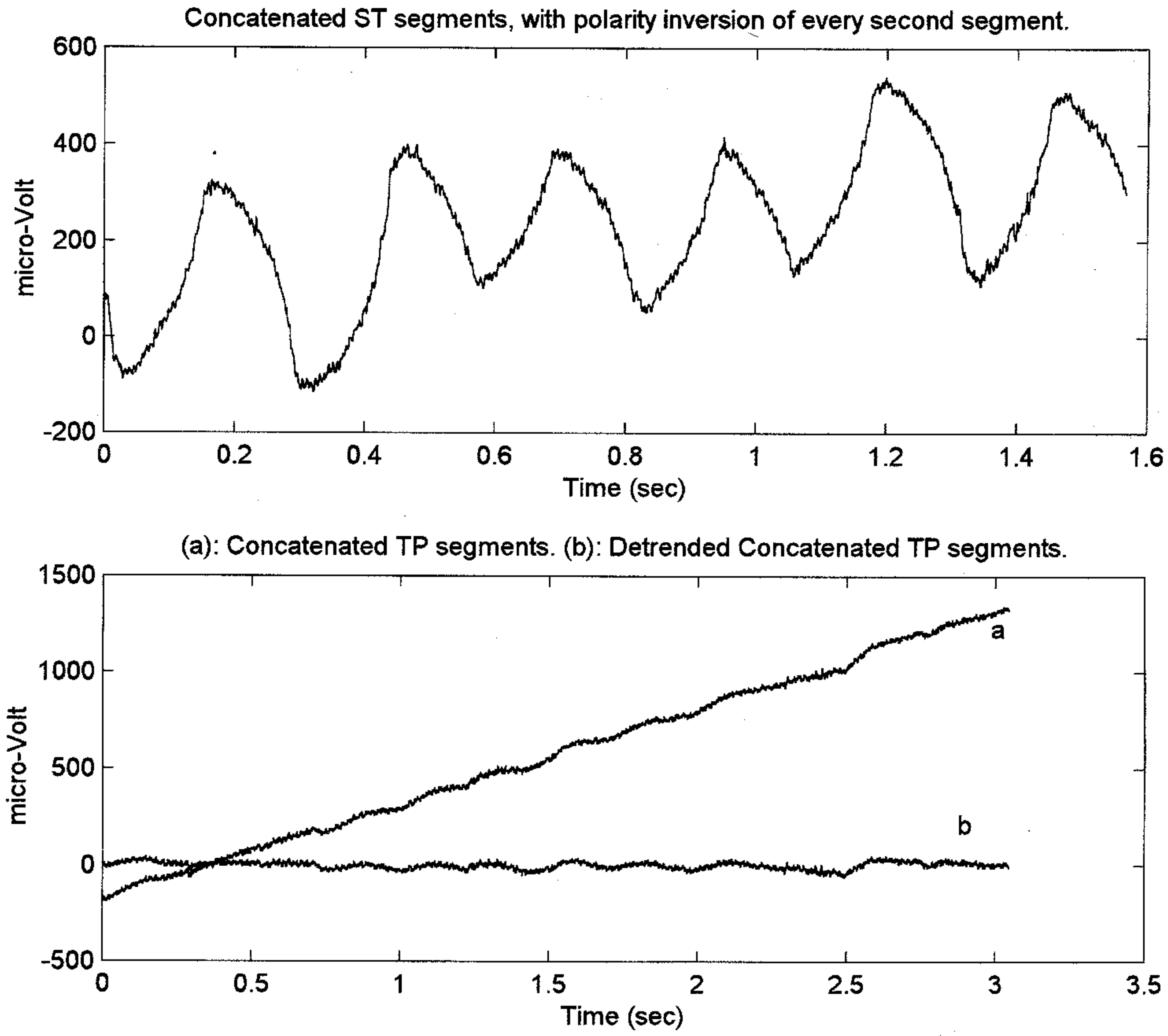

Fig. 1. Concatenated ST and TP segments.

In the right column of Fig. 2 the ST segment is represented in exactly the same manner. For instance, we observe that in the 137.8–275.6 Hz band the *RMS* value of the TP segment is 1.214 μV, whereas the corresponding value for the ST segment is 1.572 μV, an increase of 29.52% due to VLP activity. The increase goes further to 56% in the 68.89–137.8 Hz range, therefore indicating that this band retains most of the VLP energy. The *FN* is estimated by:

$$FN = 100\left(\frac{RMS_{\mathrm{TP}}}{RMS_{\mathrm{ST}}}\right)^2\% \tag{3}$$

in the scale where the larger increment occurred. This formula is not the only possible approach to the *FN* estimation. It was intuitive for us, given the definition of energy of an electrical signal. For a patient without VLP ideally $RMS_{\mathrm{ST}} = RMS_{\mathrm{TP}}$ and therefore $FN = 0\%$. The *FN* obtained in Fig. 1 is 41%. This patient had a type III VLP [15], hardly detected by the Simson method. The *FN* value is printed close to the low frequency residue, due to the shortage of available space in the overall plot. The LF residue (0–34.45 Hz) is not accounted for in the *FN* calculation since VLP should not be present. The HF residue (275.6–1102 Hz) is also discarded since it is mainly muscle noise and other HF interference. In this way, we are searching for VLP in a band that extends from 34.45 to 275.6 Hz (260.5 Hz for the musical wavelet), which includes the problematic 50 Hz line interference signal. Table 1 shows the *RMS* values of the VLP that are obtained by subtracting, in each level, the *RMS* values of the TP and the ST segments, and its distribution over the frequency bands. The percentage of VLP energy is obtained relatively to the total *RMS* of the ST segment shown in the top right corner. VLP *RMS* values seem to be rather low, but peak values may reach around 10 times more.

In Fig. 3 the same methodology, for the same patient, is applied using musical wavelets and concatenated signals as explained above. Again we note that the low frequency components, namely, those created by the concatenation process, are retained in the low frequency residue that is discarded in the *FN* computation. Table 1 summarises the results. As the frequency resolution is improved, it is possible to determine that most of the VLP energy lies in the band 68.89–97.96 Hz, a substantial refinement relative to the results obtained with harmonic wavelets. This leads to a decrease in the *FN* that halves its value to 20%, a value in better agreement with the patent's previously known condition. Table 1 also shows the VLP estimation with the Daubechies D8 wavelet [12–14]. The spectrum of Daubechies wavelets is not confined to each octave band. A great amount of overlapping occurs and each octave band exhibits replicas of decaying amplitude in the upper frequencies. Feeding the Mallat algorithm with white noise and

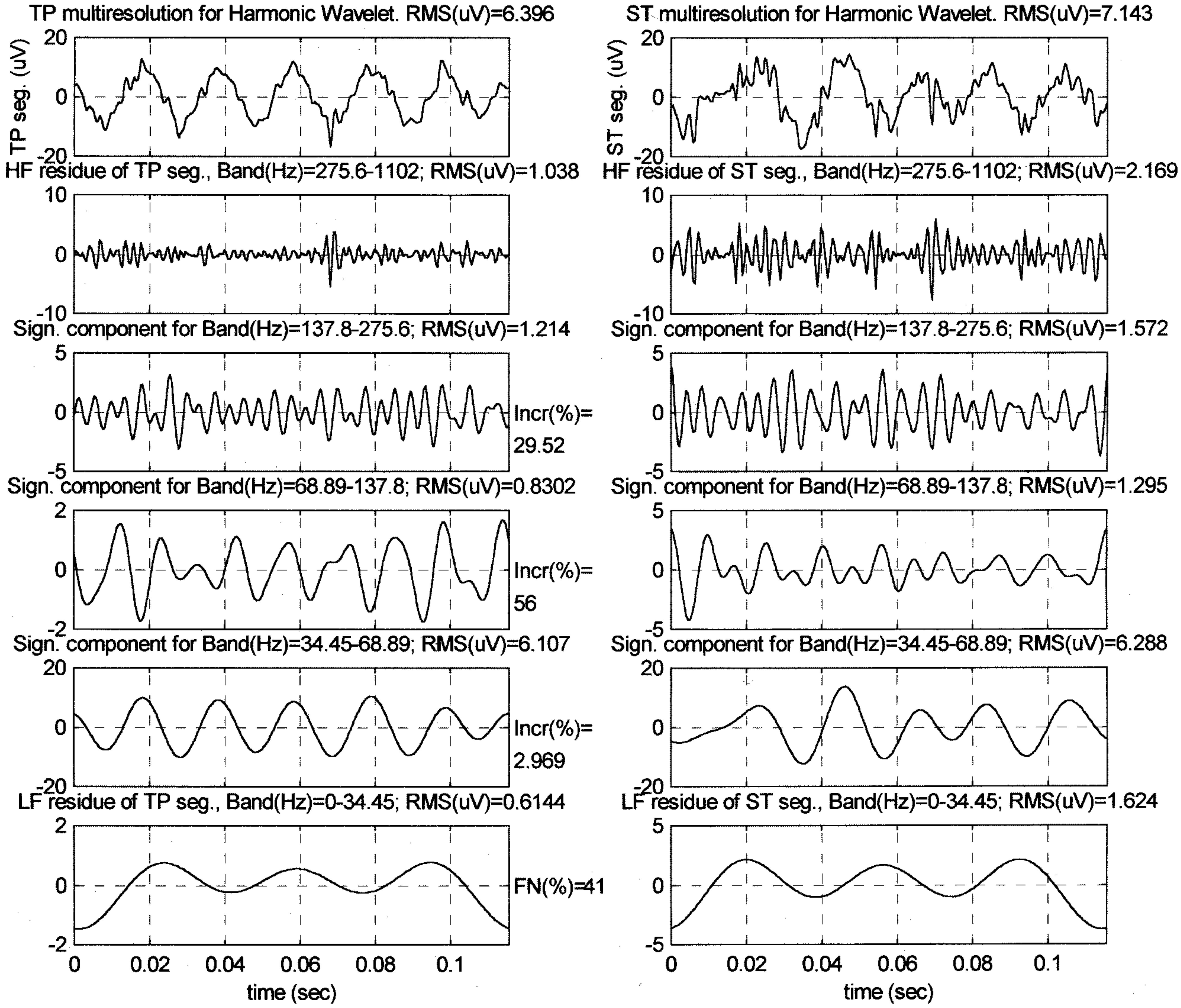

Fig. 2. Harmonic wavelet multiresolution analysis of the HR-ECG of a patient.

Table 1
VLP estimations

Frequency band (Hz)	Estimated VLP (μV-*RMS*)	% of VLP energy	% of TP to ST increase	*FN* %
VLP estimation with harmonic wavelets				
137.8–275.6	0.358	5.0	29.5	41
68.89–137.8	0.465	6.5	56.0	
VLP estimation with musical wavelets				
137.8–194.8	0.242	0.9	19.3	20
97.96–137.8	0.592	3.8	63.6	
68.89–97.96	1.026	3.8	122.5	
VLP estimation with Daubechies D8 wavelet				
137.8[a]	0.542	7.6	54.3	68

[a]Central frequency.

inspecting the spectra of the different multiresolution signals can easily confirm this. This being so, part of the energy of a particular Mallat multiresolution signal is *spread* over the others bands. This spectral *leakage* compromises the frequency analysis, since the wavelet level no longer truly represents a frequency band (is rather a central frequency), a concept so important in signal analysis. The *FN* computation is also affected since the upper wavelet levels, where VLPs are present, are corrupted with some energy coming from the lower level where 50 Hz interference lies. This behaviour explains the highest *FN* value obtained of 68%.

Although detailed results are presented here for one patient, the method gave positive and quantified VLP results in 11 patients with previously recognised VLP related cardiopathy. All these patients had been tested for VLP activity with the Simson protocol and only three were found positive. The patient in question was tested with the Simson protocol with a negative result. Since we were about to set up a method more sensitive than the classical methods for VLP detection, we submitted this patient to both our time–frequency and wavelet methods, and they produced clear positive results. We then went back and closely observed, in the time domain, the HR-ECG of the patient and found out that

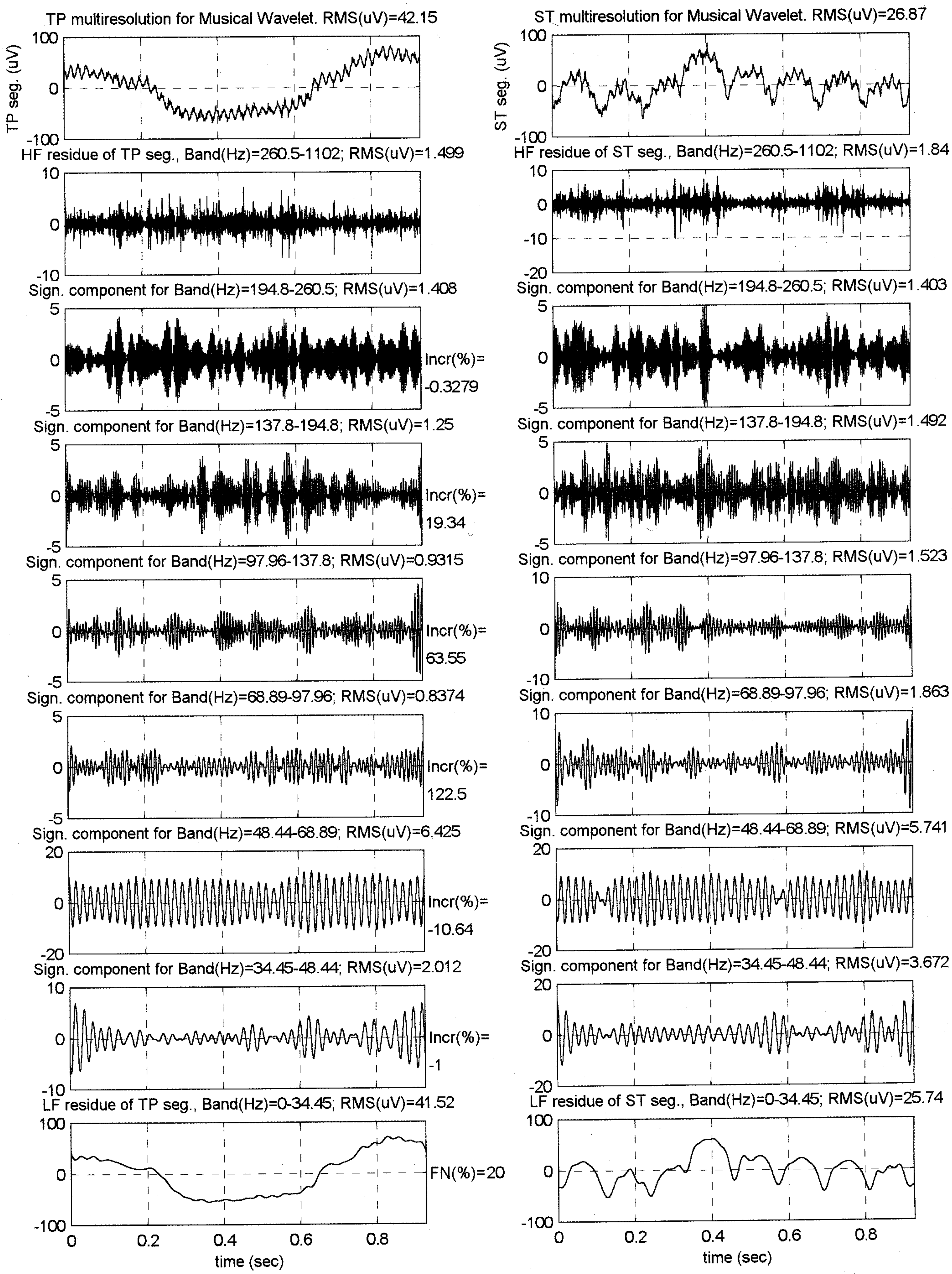

Fig. 3. Musical wavelet multiresolution analysis of the HR-ECG of a patient.

the VLP was the difficult type III [15]. Furthermore, this patient had had a heart attack a few days after having tested negative for VLP with the Simson protocol. There seemed to exist pretty strong medical evidence that this patient had VLP that was not backed up by the Simson protocol.

This patient became our reference study case, since in this paper we are concerned with the complexities of wavelet analysis of the HR-ECG and so we focused on a case that probably represents something of a 'worst possible scenario'. In addition, 17 normal subjects were used for reference and calibration purposes of the experimental set-up.

4. The interference problem

As can be observed in Figs. 2 and 3, the level of 50 Hz interference is substantial and not usually allowed in HR-ECG. Although we could have reduced it at the hardware level, we decided not to do so for testing purposes. Since this interference tends to be stationary during one heartbeat, it will appear in TP and ST segments with similar energy levels. As the method works by comparing energy levels, this interference tends to cancel in the final result. At this point the only problem resides in the sine wave phase difference between the ST and TP segments that depends on the T wave duration and is typically around 30°, equivalent to 100 ms or 5 sine periods. It may then happen that the starting values and slopes of this potential in both segments are different. The wavelet algorithm sees this discontinuity as a high frequency signal feature just as the FFT circular algorithm would, spreading its energy over the higher scale levels and therefore disturbing the estimations. Our current work includes the study of the signals edge effect and the wavelet transform algorithms. Nevertheless, bringing the 50 Hz interference to normal low levels practically eliminates the problem, and our study here concerns the worst conditions possibly occurring in a clinical set-up.

Our method requires stationary noise interference in ST and TP segments, which is a time window of around 500 ms. In this window we found that breathing muscle noise keeps essentially stationary in the majority of the beats, except possibly in cases where particular breathing patterns occur. The beats affected by non-stationary interference are discarded. Also the ST and TP segments need not be consecutive. As the breathing signal is overall periodic, the segments under study may be picked up by searching the HR-ECG record for areas where breathing muscle noise is periodically similar.

5. Conclusions

In this report we are not attempting to validate the clinical efficiency of our method, for which it would be necessary for a comprehensive clinical trial to be carried out by different research groups to be able to compare results. Rather, at this stage we are introducing a method that gave positive and quantified VLP results in 11 patients with previously recognised VLP related cardiopathy. All these patients had been tested for VLP activity with the Simson protocol and only three were positive. Moreover, we were able to estimate the VLP energy distribution in the wavelet frequency levels with a great degree of accuracy.

The HR-ECG is a highly non-stationary signal. Noise interference such as muscle noise and power line harmonics add complexity to the task of detecting and quantifying the VLP signals which also have a degree of unpredictability. Therefore, clinical evaluation of any VLP method requires substantial amounts of data representing a variety of clinical set-ups, and this is bound to be a lengthy process. It took around one decade to reasonably assess the Simson method despite its wide clinical use.

For our 11 patients, our method gave superior results and showed remarkably low sensitivity to noise. Elsewhere [12–14] we reported the use of time–frequency representations with the spectrogram and the Wigner–Ville transform to assess the results of our method of VLP analysis. We found that the multiresolution method proved to be less sensitive to the noise interference and produced *FN* values that closer depict the patients' state in our study cases, known through their previous medical history.

The 50 Hz interference in the low levels of the wavelet transform, if too high, may disturb the method, although the same level of interference would be much more disturbing of the time–frequency method and would render the Simson method impracticable.

We also used Daubechies wavelets and found that the Newland musical wavelets are more suitable for our method, due to their confined spectra that reduces spectral leakage.

We are currently looking further to apply other wavelet transform algorithms for refinement of time–frequency resolution and reduction of the signal edge effects. Also under development is an algorithm that automatically selects intervals where interference is kept stationary.

Acknowledgements

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