A Multiresolution Wavelet Method for Characterisation of Ventricular Late Potentials

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Abstract

We present a method for Ventricular Late Potentials (VLP) detection and characterisation using the Daubechies wavelets and the Newland Harmonic and Musical wavelets. The method is based on a wavelet multiresolution scheme, where the energy content of the beat-by-beat TP and ST segments of the High-Resolution Electrocardiogram (HR-ECG) are compared at different resolutions, with relative energy increases interpreted as VLP. An objective figure, the Factor of Normality, is generated for ready clinical use. These results are compared to the ones obtained with the application of the Spectrogram and the Choi-Williams Transform, using the Spectro-Temporal Mapping for the VLP study. The Factor of Normality generated by the wavelet multiresolution scheme proved to be more sensitive, in our study cases, compared to the time-frequency and the Simson methods.

1. Introduction

VLP's are cardiac micro-volt signals due to the delayed and not homogeneous propagation of the depolarisation wave through ventricular tissue. They have diagnostic value as predictors of malignant arrhythmia and cardiac arrest. The Simson time method excessively depends on the noise level and the location of the QRS limits. The Fast Fourier Transform analysis of the High-Resolution Electrocardiogram (HR-ECG), has limited success since this is a highly non stationary signal. Lander et al. [6] and Haberl et al. [5] introduced the time-frequency analysis of the HR-ECG using the Spectrogram, thus obtaining a Spectro-Temporal Mapping (STM). Other groups [1,8] performed the STM using the Wigner-Ville distribution (WVD) [2,3], to assess the VLP presence. The cross terms of the WVD are a serious limitation. If a *kernel* function is used its effect may disturb the distribution. The Spectrogram main limitations are the low resolution, lack of important time-frequency properties such as correct instantaneous frequency and marginals, and dependence of the results on the window in use. In this paper we present an alternative method based on wavelet multiresolution analysis [1,7].

2. DWT with Daubechies Wavelets

Generally, the time-scale (or time-frequency) resolution of the Discrete Wavelet Transform (DWT) is not better than the one attained with the WVD. However, frequency resolution in the DWT decreases as frequency increases, therefore increasing time resolution. We take advantage of this property since VLP's are short lived phenomena in the higher frequency spectrum. Moreover, by using DWT we avoid the problems that arise from windowing the data in the STFT and the WVD, and the severe cross terms effect in the WVD. The basic expression for the circular wavelet decomposition of a function $f(x)$ is given by [10]:

$$f(x)=a_0+\sum_{j=0}^{\infty}\sum_{k=0}^{2^j-1} a_{2^j+k}\, W\left(2^j x-k\right) \quad 0\le x<1$$

The wavelet amplitudes $\mathbf{a}_{2^j+k}$ may be obtained through the efficient Mallat *Tree* algorithm [7]. $W(x)$ are the Daubechies wavelets [4].

3. DWT with Harmonic and Musical Wavelets

In 1994, Newland [9] introduced a wavelet given by:

$$w_{m,n}\left(x-\frac{k}{n-m}\right)=\frac{exp\left(i\,n2\pi\left(x-\frac{k}{n-m}\right)\right)-exp\left(i\,m\,2\pi\left(x-\frac{k}{n-m}\right)\right)}{i\,2\pi(n-m)\left(x-\frac{k}{n-m}\right)}$$

For $m=2^j$ and $n=2^{j+1}$ the Harmonic wavelet family is obtained. Unlike the Daubechies wavelets, Newland

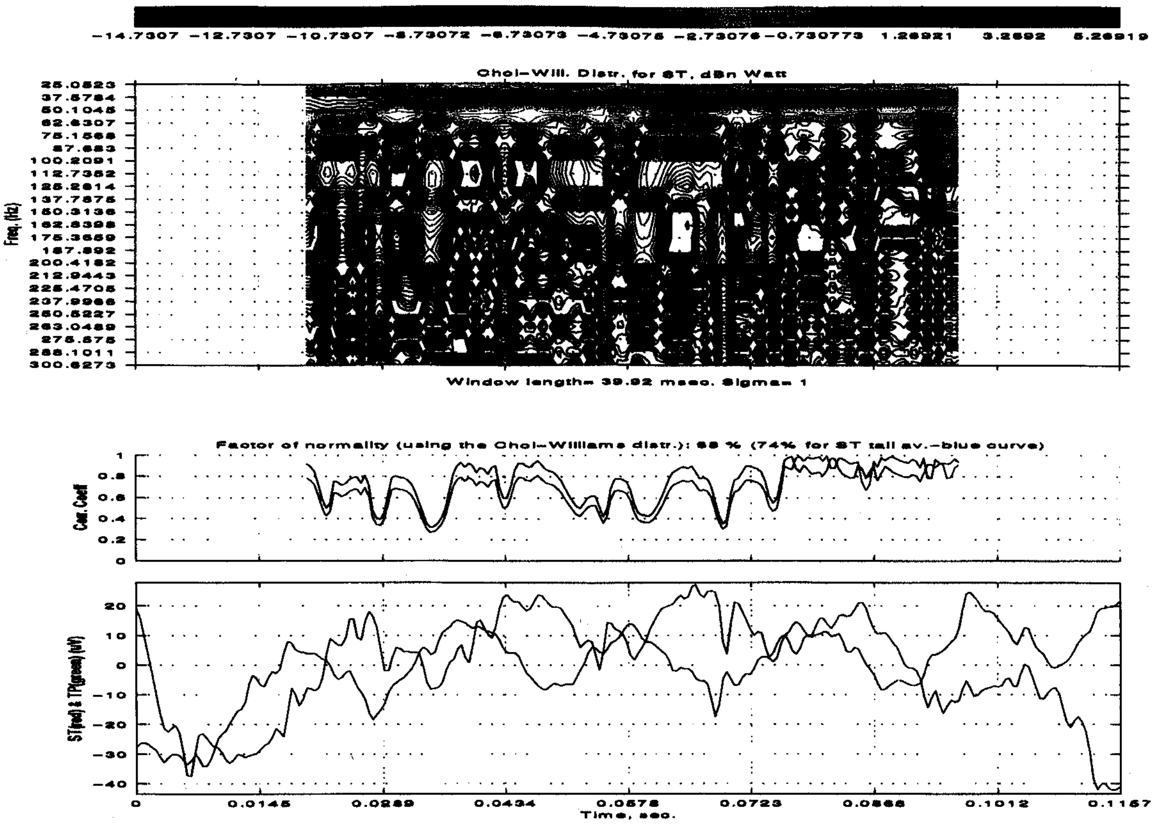

Figure 1: STM with Choi-Williams Distr. for a patient, seven days after myocardial infarction. The original figure is colour coded.

wavelets have their spectrum tightly confined, thus drastically reducing *spectral leakage*, a problem in frequency analysis of signals. The price paid for this important feature is a reduction, by about half, of the time resolution. For $\boldsymbol{m} = 2^{r/12}$ and $\boldsymbol{n} = 2^{(r+1)/12}$, $\boldsymbol{r}$ being a real integer, the Musical wavelet family is obtained, for which each octave is divided in 12 steps as in the musical scale. The frequency resolution is greatly increased with sacrifice of the time resolution, thus requiring relatively long data sets. These wavelets also exhibit a tight frequency spectrum. The DWT is performed through the Newland "sandwich" algorithm, comparable, in efficiency, to the Mallat *tree* algorithm. The multiresolution signal at a certain level is obtained by performing the Inverse Discrete Wavelet Transform with the coefficients pertaining to that level only.

4. VLP and the Choi-Williams Distribution

Haberl et al. [5] used the spectrogram of the ST segment to estimate the Factor of Normality (FN), by comparing the energy level of each time slice of the obtained STM with the average energy of the last portions of the ST segment, where no VLP's are supposed to be present. A correlation coefficient (CC) is obtained that, by integration, produces the Factor of Normality (FN). Figure 1 represents the STM using the Choi-Williams transform (σ=1), for a patient seven days after myocardial infarction, with a long, low level and broad-band VLP (type III), hardly detected by the Simson method. The FN is 68% for the CC obtained (bottom curve in the middle plot in Figure 1), using as a reference the entire TP segment. Low values of the CC correspond to higher values of the VLP amplitude. Some of the grey areas in the time-frequency plane represent VLP activity from approximately 75 Hz to 200 Hz. The resolution is very good, but cross terms scatter energy around unpredictably, thus seriously compromising the methods reliability. The original of Figure 1 was produced in colour, with a colour code bar on top.

5. Wavelet Multiresolution for VLP

The top left and right of Figure 2 show respectively the TP and the ST segments of one beat of the HR-ECG of the same patient. Below each one of these plots are the plots of the multiresolution signals in different frequency bands, shown on the top of each plot, along with the RMS values, obtained by the inversion of the DWT with Harmonic wavelets. Adding the five multiresolution

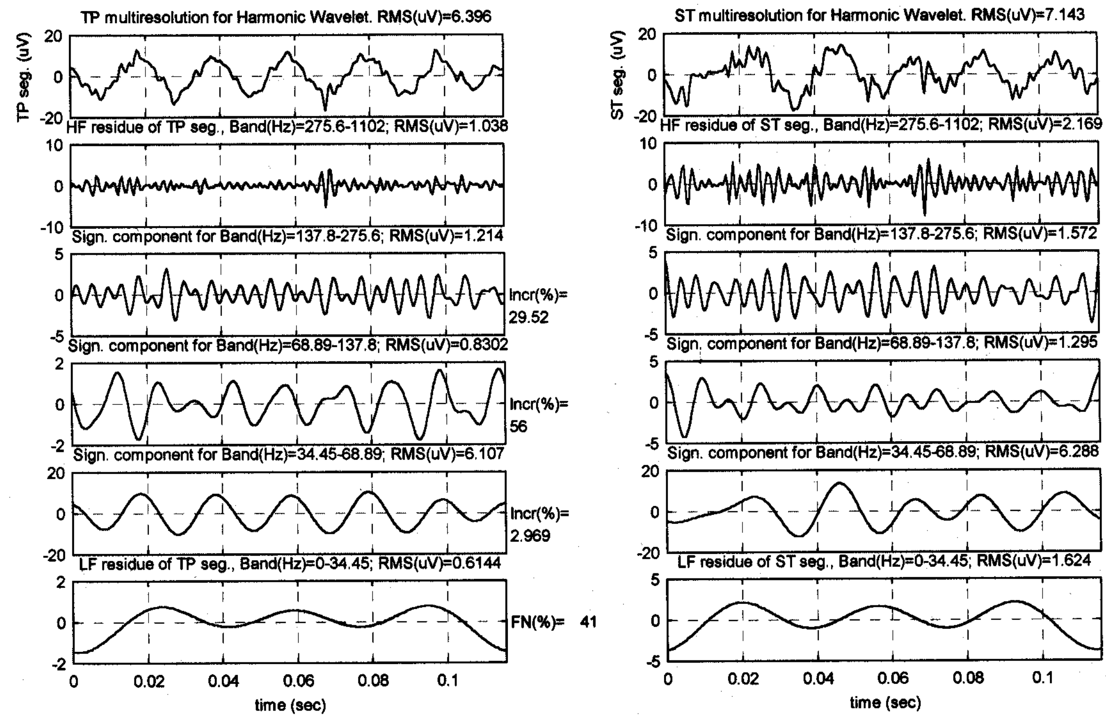

Figure 2: Harmonic wavelet multiresolution analysis for a patient, seven days after myocardial infarction.

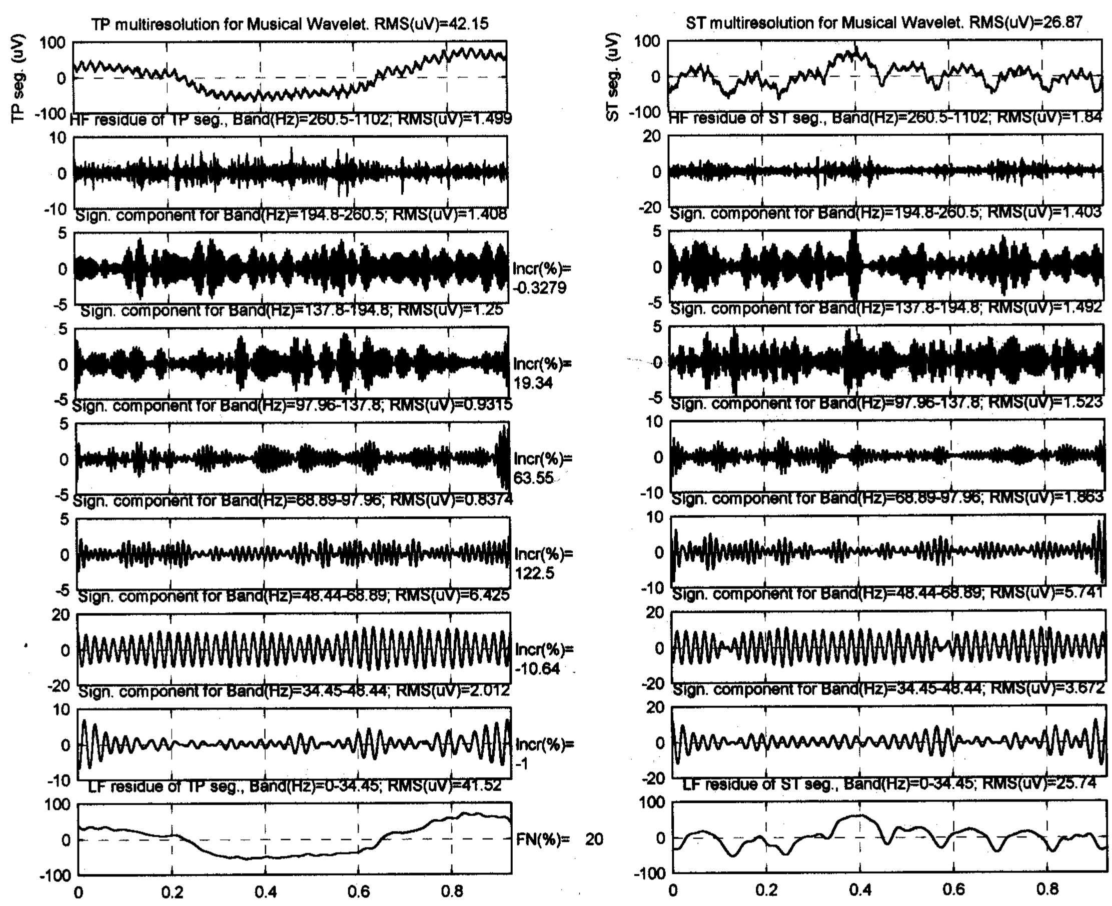

Figure 3: Musical wavelet multiresolution analysis for a the same patient, see figure above.

signals below the signal (TP or ST) produces exactly the signal itself except for computer round-off errors. Only the band 34.45 Hz to 275.6 Hz, divided in three sub-bands, is searched for energy increments between the ST and the TP segments, whose value is displayed in the middle. The FN is obtained from the level were the larger increment occurred.

$$FN = 100\left({RMS_{TP}}/{RMS_{ST}} \right)^2 \%$$

The Low Frequency residue, which is left out of the FN calculation, retains the LF components up to 34.45 Hz. The heavy 50 Hz power line noise is retained in the level 34.45-68.89 Hz and affects both segments. The high frequency residue is left out as well, and mainly contains muscle noise and other high frequency interference, although we often find energy increments in this level, indicating that VLP's may have frequency components higher than usual, perhaps at least 500 Hz. For the patient under study, the obtained FN is 41%, an improvement relatively to the spectrogram (58%) and the Choi-Williams distribution (68%). Figure 3 shows the same method using Musical Wavelets. We had to concatenate a number of consecutive ST and TP segments to overcome the low time resolution of this transform. The process of concatenation included the inversion of the polarity of every second segment to avoid sharp signal corners. The underlying LF signal is retained in the LF residue and is left out of the FN calculation. An energy increase of 122.5% and 63.55% occurs respectively in the band 68.89-97.96 Hz and 97.96-137.8 Hz. The FN is 20%, the best obtained value.

6. Conclusions

Table 1: Factor of Normality for a patient, seven days after myocardial infarction, using different methods.

Time-frequency or time-scale method	FN
Musical Wavelet	*20%*
Harmonic Wavelet	*41%*
Daubechies D8 Wavelet	*68%*
Choi-Williams ($\sigma = 1$)	*68%*
Spectrogram (Hamming Window, 39.9 ms)	*58%*

The table above summarises the results. Clearly, the best results are obtained with the Harmonic and Musical wavelets, mainly because of the very low *spectral leakage*, since 50 Hz energy *leaking* from the lower levels of the transform to the upper levels may disturb the FN result. This explains the poor result (68%) obtained with the Daubechies wavelets: spectral leakage is substantial. It should be stressed that the HR-ECG of this patient has high levels of 50 Hz noise and no signal averaging nor noise reduction techniques were used except in the hardware system. The concatenation of consecutive ST segments, a *serial* process where each beat keeps its identity, is in opposition with traditional signal averaging, a *parallel* process, where, after summation, a beat is obtained that may not represent details of individual beats. Concatenation also leads to longer data sets, convenient in wavelet signal analysis and helpful in the study of non random VLP beat to beat variations, that has physiologic and prognostic value.

Acknowledgements: The first author was supported by JNICT: BD-12-90-ID & BD-2848-94.

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