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Real time mapping QRS duration based on wavelets

***Abstract**. The pacing for permanent pacing in bradyarrhytmias can influence ventricular activation and can contribute to marked asynchrony in extremity. In this work, we search the optimal position for right ventricular pacing according the QRS duration. We evaluate the system for detection of QRS boundaries based on wavelet transform and adaptive threshold. The system is used during pacemaker implantations in Department of Cardiology, Heart Center, Hospital Podlesí Třinec.*

***Streszczenie.** W artykule zaprezentowano system do detekcji QRS bazujący na transformacie falkowej. System sprawdzono w Klinice serca w Tryncu podczas implantacji rozrusznika serca. (**Analiza w czasie rzeczywistym QRS bazująca na transformacie falkowej**).*

Keywords: adaptive threshold, QRS duration, wavelet transform.
Słowa kluczowe: QRS, transformata falkowa.

Introduction

Heart rhythm diseases are the most common cause of an unexpected sudden death in all age groups. If the heart beats too slowly, the brain and body do not get enough blood flow and variety of symptoms may results. The artificial pacemaker implanted by physicians corrects causes of slow heart beating by providing electrical signals to tell the heart to beat at the proper rates and by delivering the signal to appropriate chambers of the heart. But the stimulation can constitute risk factor of disorder signal spreading at the ventricles level and leads to asynchronous electrical activation. Right ventricular (RV) apical pacing produces a left ventricular electrical activation sequence resembling left bundle–branch block. The resulting alternation in mechanical activation may result in impaired hemodynamic performance and mitral regurgitation [4, 5]. RV apical pacing causes chronic changes in regional myocardial perfusion [6], cellular structure [7], and ventricular geometry that may impair ventricular performance [8].

This has led to an interest in alternate RV pacing site in particular the mid RV septum and the RV outflow tract septum. These sites are theoretically associated with a more physiological ventricular activation. The aim of our study was to determine the optimal site for RV pacing according the paced QRS complex duration during pacemaker implantation. The paced QRS duration can be effective indicator of impaired ventricular function. The changes in the QRS complex duration were measured by real time system. This paper describes analytical method for evaluation of the QRS duration based on wavelet transform.

Continuous wavelet transform

Fourier transform based spectral analysis is the dominant analytical tool for frequency domain analysis. However, Fourier transform cannot provide any information of the spectrum changes with respect to time. Fourier transform assumes the signal is stationary, but biomedical signal is always non-stationary. Signals recorded from the human body provide valuable information about the activities of its organs. Their characteristic shape, or temporal and spectral properties, can be correlated with a normal or pathological function. In response to dynamical changes in the behavior of those organs, the signals may exhibit time-varying as well as non-stationary responses [9]. In fact, those signals are always contaminated by drift and interference caused by several bioelectric phenomena, or by various types of noise, like intrinsic noise from the recorder and noise from electrode-skin contact. ECG signal varies in time, the need for an accurate description of the ECG frequency contents according to their location in time is essential. This justifies the use of time frequency representation in quantitative electro cardiology.

To overcome deficiency of Fourier transform, a modified method-short time Fourier transform allows to represent the signal in both time and frequency domain through time windowing function [10]. The window length determines a constant time and frequency resolution. Thus, a shorter time windowing is used in order to capture the transient behavior of a signal; we sacrifice the frequency resolution. So, an alternative mathematical tool wavelet transform must be selected to extract the relevant time-amplitude information from a signal. In the meantime, we can improve the signal to noise ratio based on prior knowledge of the signal characteristics.

The continuous wavelet transform (CWT) of a function *u(t)* (assumed to have zero mean and finite energy) is defined as a convolution

(1)

$$\widetilde{u}(a,t) = \int_{-\infty}^{\infty} \left[u(t') \tfrac{1}{\sqrt{a}} \psi^* \left(\tfrac{t-t'}{a}\right) \right] dt'$$

where: $\widetilde{u}(a, t)$ - wavelet coefficient, *t* – time, *a* – scale, the asterisk - denotes complex conjugation.

The integral measures the comparison of the local shape of the signal and the shape of the wavelet. By changing the value of the dilation factor *a*, one can zoom in and out of the signal, with *a* being a measure of the duration of the event being examined. Localization in time is achieved by selecting *t*. Thus, some time and frequency localization is achieved for each pair *(a, t)* in the wavelet half-plane. The wavelets can be normalized in such a way as to constant unit energy at all scales. Alternatively, changes in variables and different normalizations (as used below) give simpler expressions of inverse transforms and spectra [11].

Discrete wavelet transform

The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales [12].

Multi-Resolution Analysis using Filter Banks

The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal as shown in figure 1 [13]. This is called the Mallat algorithm or Mallat-tree decomposition.

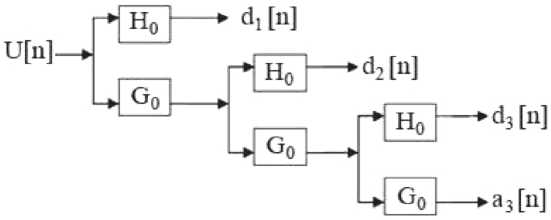

Fig.1. An example of the figure inserted into the text

Its significance is in the manner it connects the continuous-time mutiresolution to discrete-time filters. The DWT of a signal *u* is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response *g* resulting in a convolution of the two:

(2)

$$y[n] = (u * g)[n] = \sum_{k=-\infty}^{\infty} u[k]g[n-k]$$

where: *n,k* – integer.

The signal is also decomposed simultaneously using a high-pass filter h. The outputs giving the detail coefficients d_n (from the high-pass filter) and approximation coefficients a_n (from the low-pass) [14]. It is important that the two filters are related to each other and they are known as a quadrature mirror filter.

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then subsampled by 2 (Mallat's and the common notation is the opposite, g- high pass and h- low pass):

(3)

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} u[k]g[2n-k]$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} u[k]g[2n-k]$$

where: *n,k* – integer.

This decomposition has halved the time resolution since only half of each filter output characterized the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.

Prototype Wavelet Used

The large number of known wavelet families and functions provides a rich space in which to search for a wavelet which will very efficiently represent a signal of interest in a large variety of applications. Wavelet families include Biorthogonal, Coiflet, Harr, Symmlet, Daubechies wavelets [15], etc. There is no absolute way to choose a certain wavelet. The choice of the wavelet function depends on the application. Selecting a wavelet fiction which closely matches the signal to be processed is of utmost importance in wavelet applications [16].

Detection of QRS complex

The wavelet analysis of ECG signal is performed using MATLAB software. MATLAB is a high performance; interactive system which allows to solve many technical computing problems. The MATLAB software package is provided with wavelet tool box. It is a collection of functions built on the MATLAB technical computing environment. It provides tools for the analysis and synthesis of signals and images using wavelets and wavelet packets within the MATLAB domain.

The detection of the QRS complex is the most important task in automatic ECG signal analysis [17]. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment etc. can be performed [18]. A wide diversity of algorithms has been proposed in the literature for QRS detection, for an extensive review, see [19].

In the present paper we propose an algorithm based on Daubechies wavelet coefficients and subsequent adaptive threshold technique to detect QRS complex positions. Daubechies wavelet family is similar in shape to QRS complex and their energy spectrum is concentrated around low frequencies [16]. The algorithm, presented in this section, is applied on ECG signal, measured during a pacemaker implant procedure in Department of Cardiology, Heart Center, Hospital Podlesí, Třinec. The measurement procedure had following step for mapping the QRS duration. Initially the stimulation lead was placed in the right ventricle outflow tract. Then the stimulation was set up 30 bpm over the native rhythm. The lead was slowly withdrawn from the outflow tract, allowing the lead to fall toward the right ventricle apex. Finally the lead was placed in a position with the smallest pacing QRS duration.

ECG signal is sampled at 997 sample/second, and range of real frequency component of the signal is between 0,05 to 100 Hz. Main frequency components of signal are concentrated in lower frequency range 2- 40 Hz [1,2]. We found that the Multiresolution Analysis (MRA) allows us to decompose a signal into approximation and detail coefficients with desired frequency band. We perform seven-level wavelet decomposition of the resulting frequency range (table 1). We use the Daubechies wavelet D4 (db4) to obtain detail coefficients from levels 4-7. The resulting signal for tresholding is built as the sum of the absolute values of each level with final frequency band 3,9 - 62,3 Hz.

Table 1. Decomposition of original signal

	Approximation c.	Detail c.
Level 1	0 - 249,25 Hz	249,25 - 498,5 Hz
Level 2	0 - 124,6 Hz	124,6 - 249,25 Hz
Level 3	0 - 62,3 Hz	62,3 - 124,6 Hz
Level 4	0 - 31,15 Hz	31,15 – 62,3 Hz
Level 5	0 - 15,6 Hz	15,6 - 31,15 Hz
Level 6	0 - 7,8 Hz	7,8 - 15,6 Hz
Level 7	0 - 3,9 Hz	3,9 - 7,8 Hz

An adaptive threshold is initially set up as 60% of the maximum signal. The beginning of a QRS complex is detected when the resulting signal overcomes the thresholds. Then, the threshold's value adapts to the amplitude of signal automatically (Fig. 2). Threshold is continuously updated after each QRS detection using maximum of QRS complex detected (mQRS) (Fig. 3). This process has several steps:

1) After detecting of QRS complex, the blanking period is set up 200 ms to avoid oversensing T-wave and threshold is set up as 65% of mQRS.

2) Threshold decays linearly until the next detected complex or until it reaches the maximal sensitivity threshold - 30% of mQRS. The decrease takes 1000 ms.
3) The value remains for the next 1500 ms, then it decay immediately on 20% of mQRS.

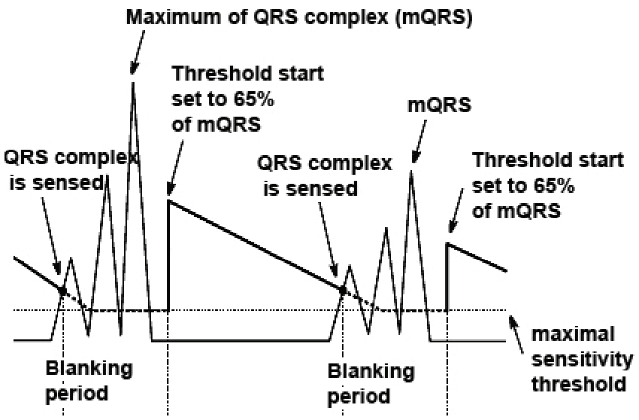

Fig.2. An adaptive threshold strategy.

The detected beginning of QRS complex is starting point for the determination positive extreme on the right in the blanking period. This local maximum is R wave (Fig. 4).

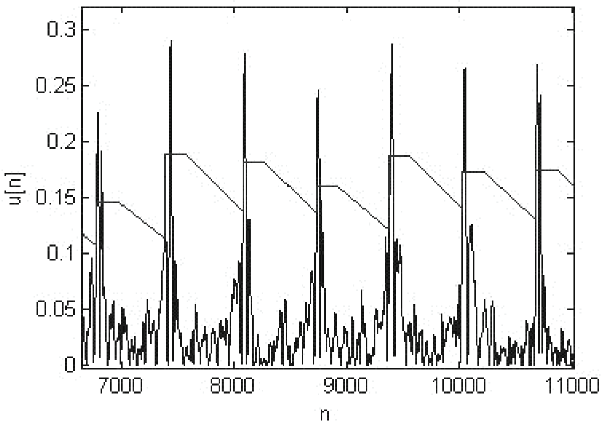

Fig.3. The resulting signal and detection threshold.

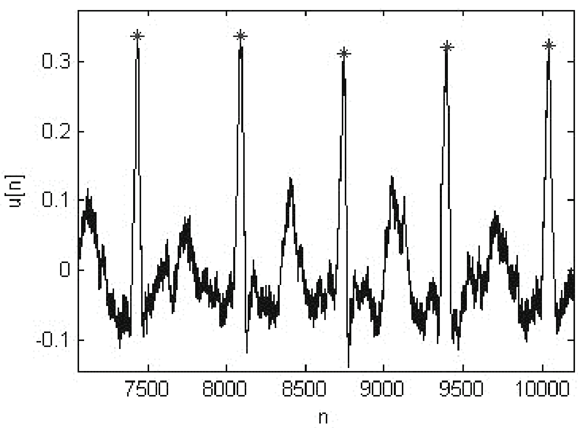

Fig.4. The original signal with detected peak of R wave

Detection QRS onset and offset

For each beat we intend to detect QRS onset and offset, we select a window around the corresponding mQRS. We locate QRS onset and offset through the relationship between zero-crossing, local maxima and minima, in the filtered signal. We apply MRA to obtain filtered signal. We use Daubechies wavelet D10 (db10) up to desired 8 level of decompositon. The filtered signal is reconstructed from detail coefficients from levels 5-8 with frequency band 2-31 Hz.

We identify the stationary points which are situated beside the zero-crossing related to mQRS, there are fiducial points to detect QRS onset and offset (Fig. 5). The first one, on the left, it is Q wave's peak, and the other one, on the right, it is S wave's peak. Finding global maxima and minima is the goal of optimization. For twice-differentiable functions in one variable, a simple technique for finding local maxima and minima is to look for stationary points, which are points where the first derivative is zero. If the second derivative at a stationary point is positive, the point is a local minimum; if it is negative, the point is a local maximum; if it is zero, and further investigation is required.

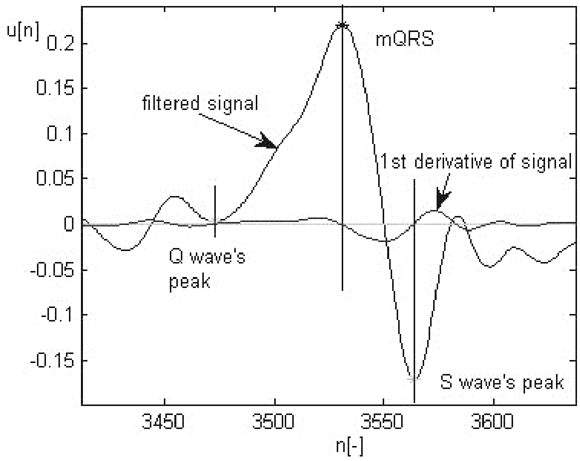

Fig.5. The technique for finding S wave's and Q wave's peaks.

The last task to detect QRS onset and offset is to locate the first critical point in magnitude located before Q wave's peak and the first critical point in magnitude located after S wave's peak. We associate these points, respectively, to the onset and offset of the complex. All necessary important points are localized and duration of QRS complex can be calculated. In figure 6 the lines represent positions of QRS onsets and offsets.

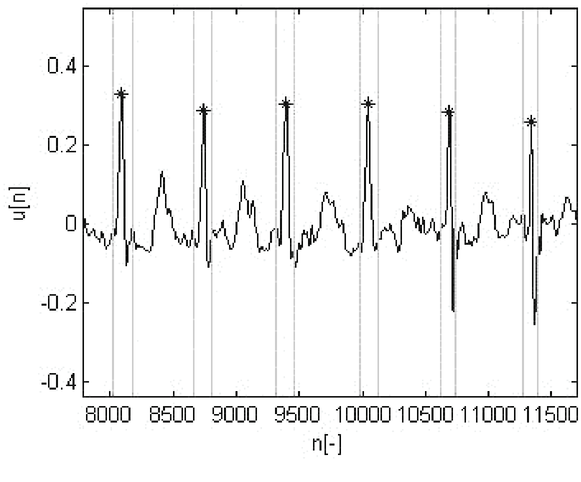

Fig.6. The filtered signal with QRS boundaries.

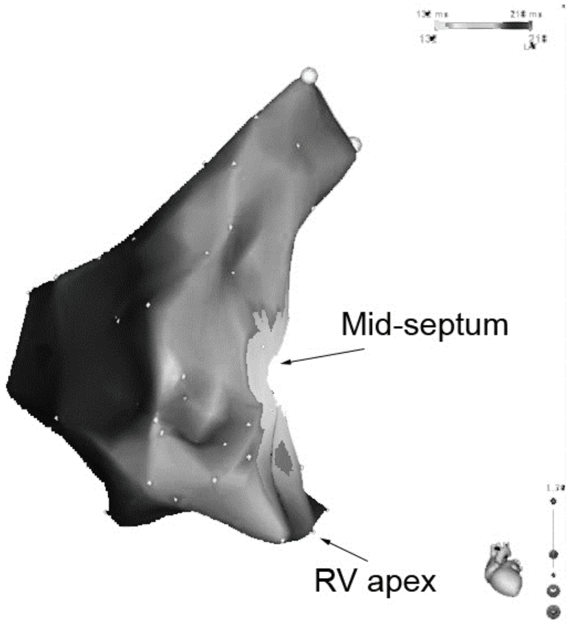

Fig.7. The 3D anatomical map with values of paced QRS duration

Conclusion

In this work we pointed out the advantage of using wavelet transform associated with an adaptive thresholding strategy for the QRS detection. Further, we took advantage of its' possibility of locating QRS boundaries in a paced ECG signal. The main advantage of this kind detection is a less time consuming analysis, so it can be used in real time signal processing.

The aim of this work was produce the system for the online evaluation of the QRS duration during pacemaker implantations. When, we searched optimal position for right ventricle stimulation with ideal QRS duration. We constructed 3D anatomical map with values of paced QRS duration with applying of Carto System (Fig. 7). The Carto is electroanatomical mapping system allows rapid orientation regarding the critical component of the reentrant circuit and supports successful and safe catheter ablation. The final map illustrated the optimal place for stimulation (mid RV septum) and confirmed our presumptions.

Our system can be used in various modifications for different clinical diagnostic a therapeutic methods, for example enhance effectiveness of biventricular treatment.

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