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Electrocardiographic signals Wavelet Transform – identification and classification properties

Streszczenie. *Praca niniejsza dotyczy badań przeprowadzonych w zakresie analizy sygnałów elektrokardiograficznych (EKG). Można by odnieść wrażenie, że natura WT prowadzi do redundantnego charakteru otrzymywanych wyników, okupionych relatywnie większą złożonością obliczeniową. Jednakże właśnie specyfika przekształceń falkowych pozwala na osiągnięcie bardzo dobrych wyników analiz zapisów EKG, co więcej nie tylko w zakresie zdolności lokalizacji, ale i identyfikacji. W pracy Autor przedstawia wyniki analizy falkowej sygnałów EKG, wraz z propozycją nieskomplikowanej metody do podstawowej klasyfikacji zespołów QRS (**Transformacje falkowe sygnałów elektrokardiograficznych – własności identyfikacyjne i klasyfikacyjne**).*

Abstract. *The paper concerns the research on wavelet transform and its power capabilities in the field of electrocardiographic (ECG) signals. One can experience that the nature of Wavelet Transform (WT) and especially Continuous Wavelet transform (CWT) leads directly to the redundancy in the outcome set. What is more it is additionally occupied by the relatively increased computation complexity. Generally it cannot be regarded as disadvantage. This said outcome redundancy and what is more important, wavelet specific form of the results, makes the WT suitable tool not only in the field of ECG signal identification but additionally in the classification purposes. In the paper Author presents the research outcomes of WT ECG signal analysis with a concept of a simple method for general classification of QRS complexes.*

Słowa kluczowe: (dyskretna) transformacja falkowa, analiza zapisów elektrokardiograficznych (EKG), lokalizacja zespołów QRS, klasyfikacja zaburzeń rytmu serca.
Keywords: Dyadic Wavelet Transform (DWT), electrocardiographic (ECG) signal analysis, QRS complex identification, arrhythmia classification.

Introduction

The results presented here in the paper summarise the Author's research on QRS complex identification and additionally classification problems. This continues investigations summarised in [1–4].

Contemporary ECG recording devices are being equipped with signal processing modules destined to compute fundamental parameters describing heart conditions. That explains the role and the need of high accuracy DSP hardware and software modules dedicated for such equipment. Computer aided analysis of the electrocardiography signal plays the essential role in the field of medical diagnostics. The fact that the heart is one of the most important organ strongly increases the importance and value of the observation and analysis results. This directly impacts the need of reliable DSP of the ECG signals – the tool that is makes heart diagnosis more accurate and helps in predicting adequate prophylaxis.

The initial and crucial as well step in the ECG signal analysis is the QRS complex detection (detection of the dominant wave in the ECG signal). This task is intensively discussed in the literature [6–9]. The nature and properties of the WT, make it potentially useful when applied not only in QRS complex localisation but additionally in specification of QRS complex morphology and arrhythmia classification. This step requires additional information on QRS complex but it seems to be already preserved within the WT results. WT results "extended" character benefits in the classification task that naturally is more sophisticated than localisation.

Available standard ECG signals databases contain beside the normal conditions registrations, wide collection of abnormalities that are also described in terms of heartbeat morphology and arrhythmias [5]. Using these information it is possible to present effects of the ECG signal WT analysis more detailed with distinguished results for different types of beats and arrhythmias.

Basics of Electrocardiography

ECG is widely used, simple, non-complex and what is the most important non-invasive medical examination. By means of this procedure one gets the set of recordings (printed or stored in computer memory) that represents the electrical activity of the subject's heart. The fundamental role of a heart is a blood pump. In details human heart consists of four elementary pumps grouped in pairs an working in series. Periodic current pulses causes heart muscle to contract, but not a whole of it at the same time. Heart excitation spreads from its top to the bottom, from the right atrium (RA) to the left atrium (LA) and next to the ventricles (left ventricle - LV and right ventricle - RV) in standard conditions. Basic anatomy of the heart is depicted in figure 1. "The flow" of a heart excitation and consequent contraction causes a pump effect - the role of a heart [1].

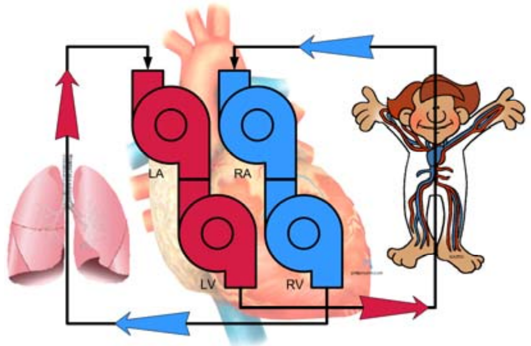

Fig. 1 Basic diagram of the human heart

The electrical activity of a human heart observed as a voltage between standard, defined test points placed on the surface of the human body results in the electrocardiogram presented in figure 2. This is a sample, standard signal presenting a healthy case. In practice there is a set of signals recorded during ECG procedure. The signals are registered from common standard parts of a human body surface. This gives a possibility of the comparable observation of a heart activity in different directions and in different planes [1].

The ECG signal can be decomposed into basic elements called waves formed by deviations from the isoelectric line (baseline voltage).

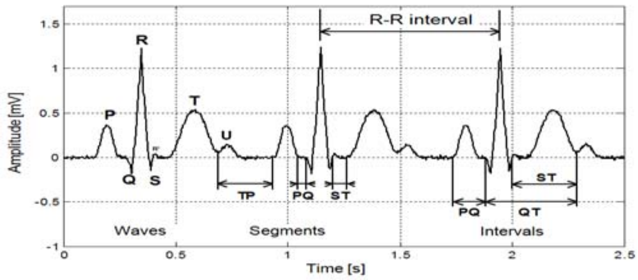

Fig. 2. Simulated, standard three cycles of ECG signal [1]

They are named: P Q R S T U in succession. Beside waves there are segments and intervals defined in the ECG signal. The former are isoelectric lines between waves and the latter include segments and waves. Amplitude and duration parameters of waves, segments and intervals carry important sets of parameters used in ECG analysis and diagnosis processes [1]. The claimed correct state of human heart makes computed parameters fall into prescribed subband of variability. Here it must be explicitly underlined that correct state of a heart does not define constant set of ECG parameters. This is obvious as a man heart differs as compared from subject to subject, what is more changes appear along the age. Additionally a man can be in a different state: rested, labored, excited or depressed. That is a reason why ECG parameters vary but still represent normal condition. On the other hand heart can fall into many dysfunctions causing cardiac arrhythmias. As it is as very complex organ, illness reasons and their symptoms are characterised by a wide variety of features. Naturally ECG recordings also receive specific form, characteristic to a particular medical condition. Based on analysis of signals included into standard databases one can notice that dysfunctions emerge in a significant change of ECG signal form. Along with normal condition recordings the MITBIH database [5] contains comprehensive set of arrhythmias. This database include recordings with: normal beats (N), left bundle branch block beats (L), right bundle branch block beats (R), atrial premature beats (A), aberrated atrial premature beats (a), nodal (junctional) premature beats (J), supraventricular premature beats (S), premature ventricular contractions (V), fusion of ventricular and normal beats (F), atrial escape beats (e), nodal (junctional) escape beats (j), ventricular escape beat (E), paced beat (/), fusion of paced and normal beats (f), unclassifiable beats (Q) and additionally isolated QRS-like artifacts (|).

Wavelet transform tool proved its usefulness in the task of QRS complex detection not only for the normal beats but also for each other morphology mentioned above. It turns out that it is also suitable in classification purposes [3, 4]. This is one of the profits for a relatively increased computational complexity. There are several abnormal types of QRS beat, as depicted above, but the ventricular beats are of the fundamental importance. They include both: premature ventricular contraction – V and ventricular escape beat – E (fig. 3). These type of arrhythmias occur commonly and they can make a real threat. That is a reason these types of arrhythmias are within the scope of the classification process performed by medical devices, yet at the beginning of ECG digital signal processing. Wavelet transform potential can be efficiently used in such classification of detected QRS complexes.

Results presented in [2] revealed the ability of WT in the field of distinguishing different types of QRS beats, including of type V and E (ventricular morphology). Not only Continuous Wavelet Transform can be applied in this task. This is important as CWT is a CPU power consuming tool. DWT also presents suitable properties as used in QRS complex classification.

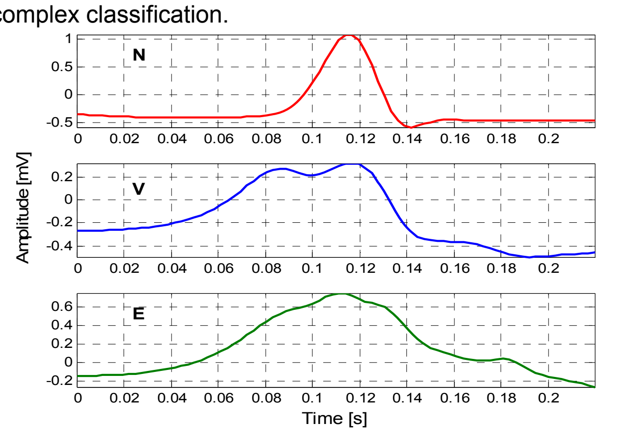

Fig. 3. Correct sinus rhythm QRS complex **N**, together with common arrhythmia types: Premature **V**entricular contraction and ventricular **E**scape beat. Waves presented in the figure were taken from [5] and averaged

Wavelet Transform Fundamentals and Wavelet based ECG signal analysis approach

Wavelet Transform (WT) is defined by the equation (1)

$$(1)\quad W_{\psi,f}(u,s)=\left\langle f(t),\psi_{u,s}(t)\right\rangle=\int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)dt$$

where: W – wavelet coefficients, Ψ – wavelet function, *f(t)* – function to be analysed, u – translation parameter, s – dilation (scale) parameter.

The *Quadratic Spline* wavelet is commonly used in ECG signal analysis. In general, as scale parameter s is continuous (Continuous Wavelet Transform) one gets the results in corresponding time-scale space. An example of ECG signal (lower picture) together with CWT coefficients for scales up to 128 (upper picture) is presented in figure 4.

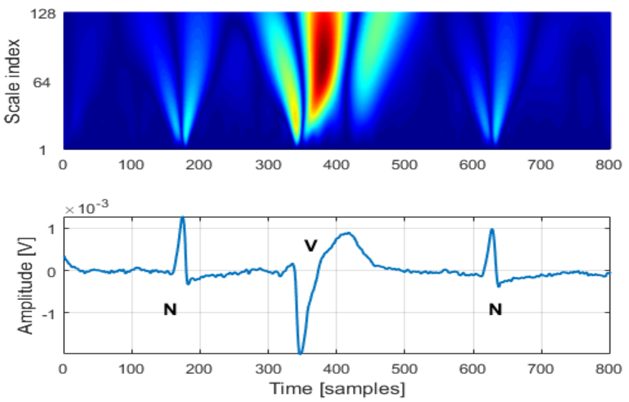

Fig. 4. A sample type V QRS complex (the middle ECG cycle) taken from the database [5] together with CWT results computed for 128 scales and with a use of *Quadratic Spline* wavelet

The main difference between normal type (N) and ventricular type (V) QRS complex can be seen in the amplitude range as well in the scale range, as investigated in the CWT coefficients distribution. One can see in the figure 4 that the amplitudes of the CWT coefficients for the V type QRS are much higher as contrasted to the N type QRS CWT coefficients. What is more V type QRS CWT coefficients are shifted towards higher scales (lower frequency band) as compared to the N type QRS coefficients. This hint that was used in the proposition of DWT based discrimination (classification) of two main QRS morphologic types.

Solutions presented in the literature [7–9] utilises Adaptive Wavelet Transform to analyse ECG signals. Mostly the tool is used to increase QRS complex detection accuracy. Approach presented in [8] attempts to discriminate normal and abnormal (arrhythmic) QRS types. In most cases additional tools like, artificial neural networks, genetic algorithms, prediction and of course least mean squares minimisation are used. Recent Author's research results showed that wavelet coefficients themselves can be useful in distinguishing normal and arrhythmic QRS beats. As the QRS classification problem is concerned, the minimum common requirement of contemporary ECG recorders is the detection of ventricular QRS beats. On the other hand many recorders are not based on strong computational productivity architectures. That is why Author decided to look closer into the Wavelet coefficients representing different QRS morphologies. Based on that Author proposed an idea of distinguishing different QRS types. Additionally there is a potential possibility of on-line wavelet filters modifications to increase detection SNR.

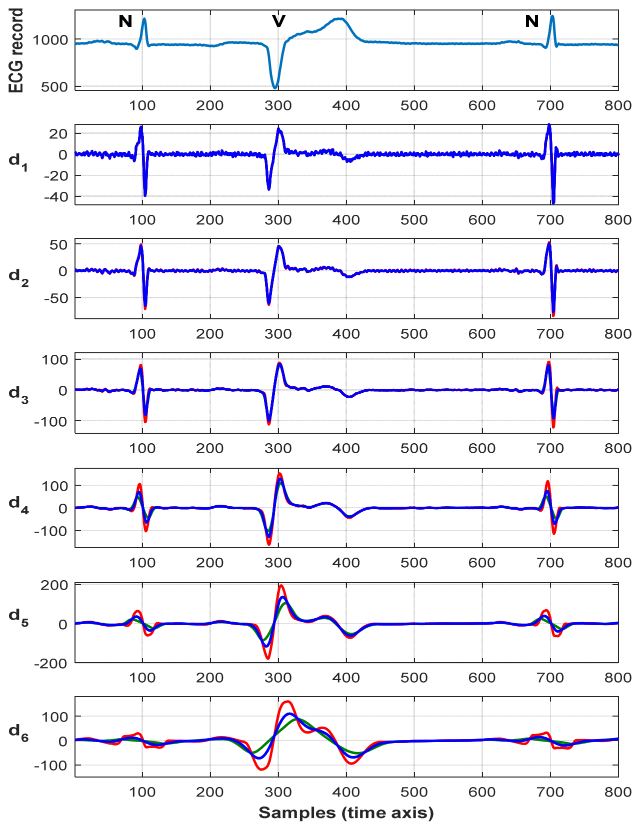

Fig. 5. Sample of ECG recording taken from MITBIH database [5] with both QRS type N and type V. DWT coefficient were calculated for 3 different wavelet based filters (the original QS and 2 Author's propositions) plotted in blue, red and green

Research

All computations were performed for signals taken form MITBIH database sampled at 360 Hz. In practise during identification stage it is sufficient to narrow down the WT scale set to the given range for the particular sampling frequency. For the classification purposes to increase WT ability of QRS complex morphology recognition one can utilise WT alternative properties. First, different set of WT scales may be taken into the account to emphasize the properties of different morphologies of QRS complexes. Second, different wavelets can be used during WT computations.

Author used mainly different proposed wavelet based filters during recent research, but the varied set of computed scales was not excluded (fig. 5). Additionally different WT filter lengths were tested [3]. It turns out that the techniques mentioned above can be (even should be) used together.

Figure 5 presents a sample ECG signal containing both normal QRS complexes (type N) and a ventricular QRS complex (here, type V). The DWT coefficients were calculated three times for different wavelet based filters. This time only blue plot is analysed as it represents WT coefficients computed and plotted for the original Quadratic Spline wavelet. Analysis of this sample signal WT together with the CWT coefficients presented in the figure 4 shows general dependency. For high frequency bands (scales d_1 - d_2) both types of QRS complexes have got almost the same representation of WT coefficients in terms of their amplitudes. Time dependencies of the coefficients are different for these QRS types. They can be used to differentiate QRS of N and V type. Amplitude differences arise from scale d_3. They only increase for scales d_4 - d_6. This is justified as one calculates and analyses frequency spectra of averaged N and V types QRS complexes (fig. 6).

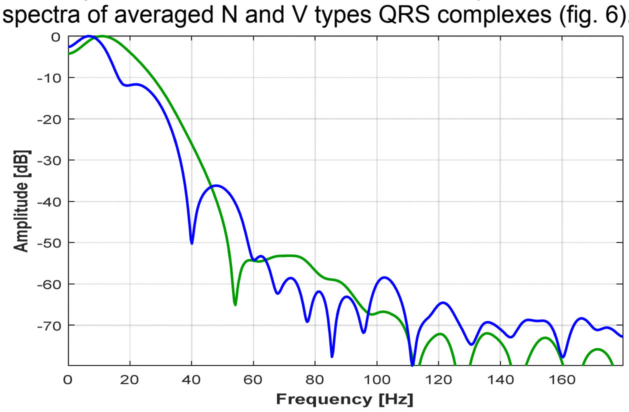

Fig. 6. Frequency spectra of the MITBIH database [5] averaged QRS complexes: Normal (green) and Ventricular (blue) beats

Main energy is concentrated at lower frequencies for the V type QRS complex as compared to the coefficients of QRS of type N (Fig. 6). This explains why the amplitudes of WT coefficients for V type QRS complexes are higher than the respective values for N type QRS complexes for increased scale indexes (d_3 – d_6). This property makes WT the useful tool in QRS classification purposes. To emphasise this feature Author decided to modify computations by changing the parameters of Quadratic Spline FIR filters. The experiments were mainly focused on the modification of the filters values with the filters length left unchanged. The variable filters lengths were also used independently in [3].

Proposed set of modified Quadratic Spline WT filters, which is based on the original scaling QS function that values were modified consecutively by a predefined additive factor. The operation was performed with the scaling function condition (2).

$$\sum_i h_i = 1 \tag{2}$$

where: h – scaling function filter coefficients, i – coefficient index.

As a result collection of filters starting from filter with coefficients equal to [0.25 0.25 0.25 0.25], through original QS scaling function [0.125 0.375 0.375 0.125] and ending with [0 0.5 0.5 0] filter were achieved. Outcomes are presented in the figure 7, where the first mentioned above filter is plotted at index 0, the second one at 25 and the third one is plotted at the index 50, respectively. Filter modifications implied evident changes in its frequency spectrum what can be observed in the figure 8.

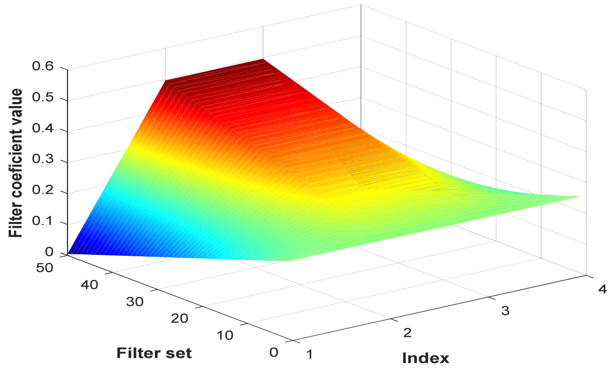

Fig. 7. Modifications of Quadratic Spline scaling function (original filter set at index 25)

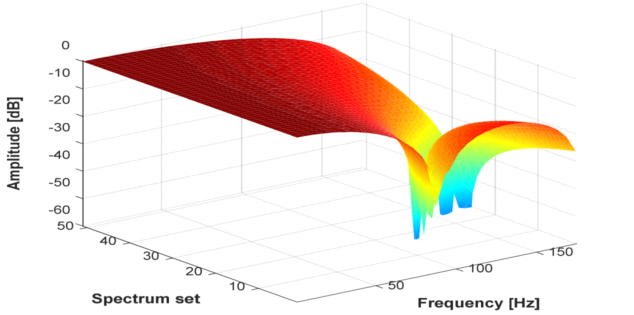

Fig. 8. Frequency spectra of modified Quadratic Spline scaling function (original spectrum at index 25)

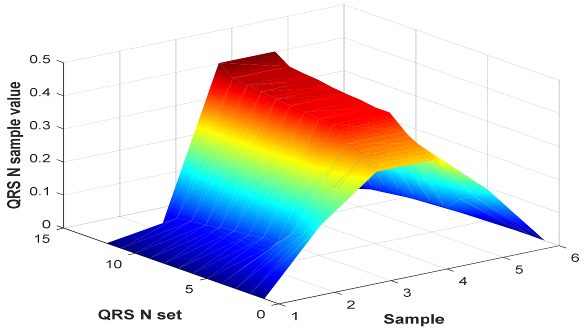

Fig. 9. Sample of averaged QRS type N complexes taken from MITBIH database [5]

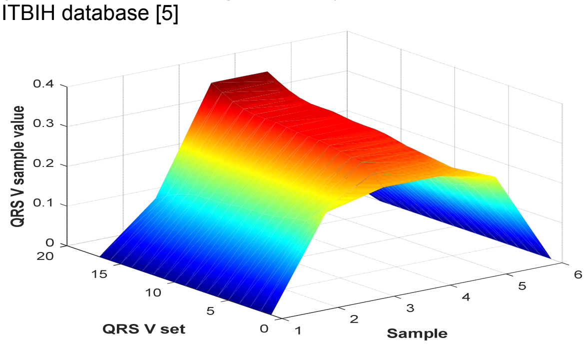

Fig. 10. Averaged QRS type V complexes taken from MITBIH database. Recordings were selected as they include significant number of ventricular type beats

The fundamental aim of the experiments carried out by Author was to fit the WT computations to the ECG signal analysis requirements with least possible changes. In this case changes of the QS scaling function were made to find a match to the elements of ECG signal, here to the QRS complexes. The guiding light was QRS complex form taken from the real signals. To illustrate this idea representative recordings containing N type QRS complexes were selected. Recordings with V type QRS complexes were selected independently. After that, for each recording, extracted complexes were averaged and the results were presented in the figure 9 and 10.

What was to be expected, QRS complexes both of type N and V can vary as compared recording to recording. Of course difference between N type and V type is more significant. I can be clearly seen in the wave field difference, computed as the multiplication of time and amplitude (even if normalised as in the figures).

Differences in parameters of N and V type QRS complexes can be observed also in WT coefficients computation as it was already presented in the figure 5. Additionally the transform was computed for modified QS scaling filter: [0 0.5 0.5 0] plotted in red and [0.25 0.25 0.25 0.25] plotted in green (fig. 5). From the QRS detection point of view it is remarkable that an interesting property appears especially for the red plot. For the scales d_3 - d_6 additional amplitude gain can be observed as compared to the outcomes based on original QS scaling filter (blue). Coefficient amplitudes are even 50% higher for the scale d_6 in the case of QRS type V complex. This is a promising property for the QRS classification especially for the ventricular type which is the one significant importance.

Conclusions

Wavelet transform tool proves to be very effective and useful tool not only in the QRS detection procedure but also the classification process especially as ventricular excitations are considered. It appears that analysis of defined set of scales can be a source of both identification and classification parameters. Modifications of the filters used during WT calculations can additionally emphasize the particular QRS complex type parameters. Initially predefined set of filters was used the Author's research. But this not excludes application of a feedback making it possible to change WT filter dynamically according to the form of the identified and even classified QRS complex.

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