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Evaluation of the QRS complex wavelet based detection algorithm

Abstract. *The article concerns the problem of computer aided electrocardiography signals analysis. Automatic analysis of these signals starts with QRS-complex detection which is the principal task. Reliability rate achieved at this stage affects all ECG signal parameters determined at the following steps of automated analysis process. This fact proves that the first stage of ECG signals analysis is of high importance. Detailed discussion of obtained results plays the main role of the article.*

Streszczenie. *Artykuł dotyczy problematyki występującej we wspomaganej komputerowo analizie sygnałów elektrokardiograficznych. Podstawowym zadaniem, które rozpoczyna analizę jest detekcja zespołów QRS. Wiarygodność wyników otrzymanych na tym etapie, bezpośrednio wpływa na jakość parametrów wyznaczanych na etapach kolejnych. W artykule przeprowadzono dyskusję i szczegółowy opis wyników. (**Ilościowa ocena algorytmu do lokalizacji zespołów QRS, opartego na przekształceniu falkowym**)*

Keywords: ECG signal automated analysis, QRS complex detection, discrete, dyadic wavelet transform
Słowa kluczowe: wspomagana komputerowo analiza zapisów EKG, detekcja zespołów QRS, dyskretna, diadyczna transformacja falkowa

Introduction

The article contains analysis of the results of the QRS complex detection in ECG signal for the author's algorithm based on Dyadic Wavelet Transform applied.

Computer aided analysis of the electrocardiography signal is of very high importance in the field of medical diagnostics. As the heart is one of the most important organ and its condition seriously affects functionality of the rest of the human body, the availability of the reliable diagnosis and the helpful tools is strongly desired. That is straight reason of the wide popularity of the applications for the computer-aided medical observations. As the heart diseases are one of the main reasons of human mortality, the discussed problem gains its range. In the field of the electrocardiography there is the still need for the robust and credible application tools, that would make it possible not only to diagnose heart muscle abnormalities but to carry out widely defined prophylaxis. Electrocardiographic signals analysis and QRS complex detection (the dominant wave in the ECG signal) is well discussed in the literature. However, the results are mostly presented in the synthetic form by a single parameter for a whole signal (commonly it is *error rate* - *ER*). Available standard ECG signals databases contain beside the normal conditions registrations, wide collection of abnormalities that are also relegated and described in terms of heartbeat morphology and arrhythmias. Using these properties it is possible to present effects of the ECG signal analysis more detailed with distinguished results for different types of beats and arrhythmias. This is very helpful in research concerning particular properties of the detection algorithm, showing its strengths and weaknesses.

Electrocardiography background

Electrocardiography (ECG) is a very common, simple and non-invasive medical examination. Its result - electrocardiogram is a recording (printed on paper or displayed on the monitor screen) illustrating electrical activity of a patient's heart. The heart is a pump, periodically self excited by tiny pulses of current, generated by specialized cells located inside the organ. 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.

Fig. 1 Basic anatomy 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 are more than one signal recorded during ECG examination. The signals are registered from different parts of a human body surface. This gives a possibility of the observation of a heart activity in different directions and in different planes.

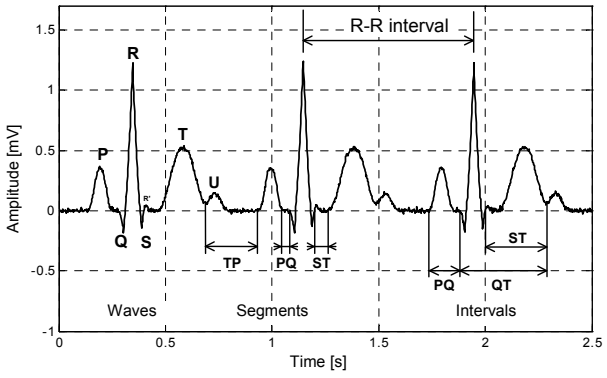

Fig. 2. Simulated, standard three cycles of ECG signal [3].

One can decompose the ECG signal into basic elements called waves formed by deviations from the

isoelectric line (baseline voltage). They are named: P Q R S T U in succession. The P wave reflects sequential activation (depolarisation) of the right and next, left atrium. It is followed by the QRS complex that is an electrical representation of ventricular depolarisation. There is a T wave at the end of single cycle ECG signal and it represents ventricular repolarisation - return to its resting state. One more wave can appear in ECG recording. It is an U wave, but the origin for this wave is not clear. It is only mentioned here for the sake of completeness of ECG components. 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. Both of them carry important sets of parameters used in ECG analysis and diagnosis processes.

The automatic analysis of ECG signals is a very helpful, often even required practice in cardiac disease monitoring and diagnosis process. As the QRS complex is commanding and the most important wave in ECG cycle the automatic analysis starts from detection of this wave. Precise detection of the QRS complexes is of a high importance, as their positions are directly used in determining fundamental parameters such as *Heart Rate* and *Heart Rate Variability*. The positions serve also as fiducial points in the following stages of the automatic ECG analysis focused on P and T waves detection and segments and intervals properties determining. Sets of parameters including amplitudes and polarity of waves, their time durations as well as time durations of segments and intervals serve as input values for computer aided diagnosis procedures.

Wavelet Transform Fundamentals and Wavelet based ECG signal analysis approach

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

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

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

In general, scale parameter s is continuous (Continuous Wavelet Transform) and the signal is analyzed in corresponding time-scale space. An example of ECG signal (lower picture) together with CWT coefficients at scales from 1 up to 64 (upper picture) is presented in figure 3.

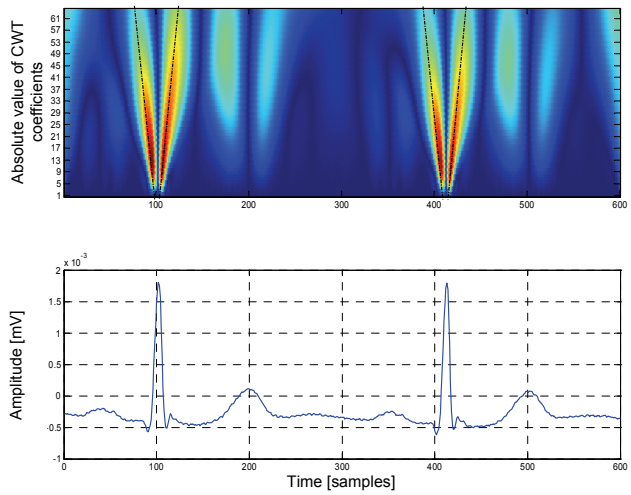

Fig. 3. CWT coefficients of a two cycles of real ECG signal.

The wavelet used in computations is the quadratic spline wavelet. Its properties, i.e. associated filters of the wavelet have a linear phase, make it very useful in applications of ECG signal analysis including QRS complex detection. One can see (in the upper picture in the Fig. 3) that there is a pair of local extreme areas present in the neighbourhood of each QRS complex. These extremes are presented in absolute values in the figure 3, but actually there is a pair of extremes of the opposite signs at each of scale. What is more and not less important the set of scales at which extremes are present is strictly defined, characterising the QRS complex. These extremes form maxima and minima lines, respectively. (dashed black line in the Fig. 3). The analysis of the extremes in terms of: the amplitude, the distance within the pair as well as the distance between extremes at adjacent scales and finally an information on how these extremes propagate within a single extreme (maxima or minima) line, creates a set of input data for the decision of QRS complex detection in the input signal.

Continuous approach to the wavelet transform often makes information represented by the output coefficients redundant. This is also valid to the QRS detection problem. That is why many of the developed algorithms for this purpose are based on wavelet transform with not continuous but decimated and consequently narrowed down set of scales [9]. What is more, the implementation of fast algorithms needs the scale parameter to be discrete. That is why in practice the s parameter is discretised along dyadic sequence $(2^j)_{j\in C}$ [5]. It is Dyadic Wavelet Transform (DWT) in this condition. There are of course some solutions presented in the literature, based on CWT. Dyadic Wavelet Transform is a very effective mathematical tool in a wide spectrum of applications including detection and analysis of rapid changes in signals. This embraces biomedical signals with ECG signal analysis, naturally including QRS complex detection. Wavelet transform is very well suited for this purpose. There is a single QRS complex above DWT coefficients, presented in figure 4 for a narrowed scales set.

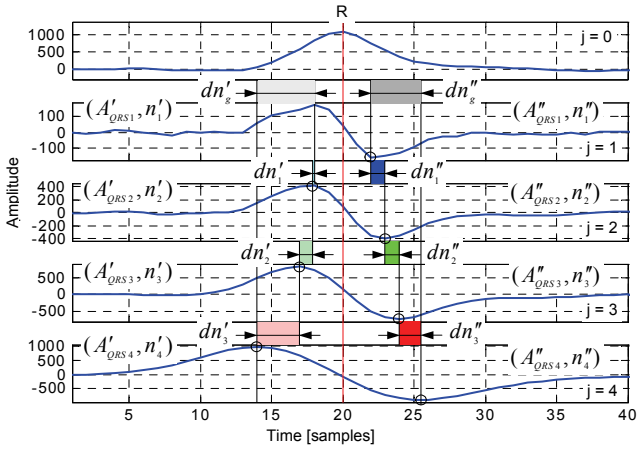

Fig. 4. Single QRS complex with DWT coefficients and calculated parameters for the QRS complex detection process: A - amplitude of the extreme (minimum or maximum) ; n - extreme sample index; dn - distance between two extremes from adjacent scales within a single extreme line.

The developed algorithm is an modification of [6] and in details was presented in [1,2,3]. The essential explanation together with properties that are specific and original in the proposed approach are discussed in the paper. For the QRS detection purpose the range of scales is chosen so that their frequency spectra cover the spectrum of the

average QRS complex, obtained from the complete set of QRS complexes present in standard database [4]. For the sampling frequency of the signals in the [4] four scales (called characteristic scales) cover the mentioned averaged QRS complex spectrum. Analysis starts from the coarsest scale 2^j (where $j = 4$) that is characterised by the best frequency resolution what implicates least signal details along with the best QRS complex to other ECG waves as well as most artefacts components ratio. Each QRS complex at each characteristic scale is represented by a pair of local extremes of opposite signs, amplitudes exceeding threshold defined for that scale and the extremes are placed in the local neighbourhood relevant to the time properties of QRS complex (Fig. 4). Thus at the 2^j scale (where $j = 4$) there is a pair consisting of a local maximum of an amplitude A'_{QRS4} and position n'_4 and of a local minimum of an amplitude A''_{QRS4} and position n''_4. Based on the QRS detection initial data gathered at the 2^4 scale, within the neighbourhoods dn'_3 and dn''_3 QRS detection procedure is continued at the 2^3 scale resulting in determining parameters A'_{QRS3}, n'_3 and A''_{QRS3}, n''_3 respectively. The analysis finishes at the finest scale 2^j (where $j = 1$) which in turn is characterised by the best time resolution. This fact is very helpful in QRS complex time precise localisation. The additional condition used in QRS detection process defines a pair of global neighbourhood parameters dn'_g and dn''_g describing maximum distance between extremes positions in a single extremes line. The complete set of parameters A and n acquired from all the characteristic scales accounts for the essential condition of the decision of QRS complex presence in the input analysed ECG signal. Additional procedures are applied in order to reach better coefficient of reliability These are: redundant extreme rejection [2,6], *Lipschitz regularity test* procedure to reject QRS looking like artefacts [2,5,6]; *blanking* which is natural as after each ventricular muscle contraction (QRS complex observed in ECG signal) there is anatomical period of time (*refractory period*) during which no subsequent contraction is possible [2,6] and finally *searching back* technique [2,6] which is very helpful in all cases when no subsequent QRS complex is found within defined period of time following the previous QRS detection. This enables threshold coefficients values change to make the algorithm more sensitive.

The presented algorithm [1,2,3] was developed based on the one described in [6] but there are many crucial properties that distinguish it from the "master" algorithm. These are: length of data buffer analysed in a single iteration is calculated upon instant parameters of the ECG signal being processed; only a single QRS complex is searched in a single iteration; threshold is not a single value but a variable function; final QRS complex detection decision is made after additional neighbourhood analysis - this provides for *refractory period*, mentioned before and is used to prevent from detecting QRS similar portions of signal or artefacts placed near effective QRS complexes and omitting the latter ones; *searching back* technique is performed by means of cycle repeated operations with iteratively decreasing threshold (this time threshold is a single value).

Results

Evaluation of the proposed algorithm was performed with a use of The MIT-BIH Arrhythmia Database - Third Edition [4]. At the QRS complex detection stage all the necessary information consists of the reference positions of QRS complexes in the database analysed signals. At the time there is no QRS complex morphology specification and analysis. Here one must say that beside normal QRS complexes there are a lot of abnormal forms (i.e. atrial premature beat or premature ventricular contraction). The most important object is to find all QRS complexes only, at the initial stage of ECG signal analysis. No classification is performed at this stage. On the other hand statistical experiments and evaluation concerning more detailed information can be of high importance. It reveals helpful data in researches focused on error rate decreasing of the proposed solution. The presented algorithm was tested with a use of signals from MIT-BIH Arrhythmia Database [4], with different types of arrhythmias depicted. This allows one to carry out research taking into account this additional data, instead of QRS-complex position only. The approach is very useful in evaluation of the proposed solution of QRS complex detection not only at the presence of anatomic, sinus rhythm but also during other incorrect episodes suggestive of cardiac muscle dysfunctions.

Moreover, analysis of the algorithm "internal states" in terms of wavelet coefficients of QRS detection results for different types of heart beats can be very valuable as well. It can play the essential role in the initial evaluation of the algorithm capability for the problem of beat classification based only on the wavelet algorithm results.

The reference database [4] contains information on positions of QRS complexes and their morphology (beat type) which includes (together with database [4] annotations used in Fig. 5): normal beat (N), left bundle branch block beat (L), right bundle branch block beat (R), atrial premature beat (A), aberrated atrial premature beat (a), nodal (junctional) premature beat (J), supraventricular premature beat (S), premature ventricular contraction (V), fusion of ventricular and normal beat (F), atrial escape beat (e), nodal (junctional) escape beat (j), ventricular escape beat (E), paced beat (/), fusion of paced and normal beat (f), unclassifiable beat (Q), isolated QRS-like artifact (|). There are episodes of ventricular flutter also included in the database [4]. Because detection of this wave is very important it became a separate processing task in ECG signal analysis specialised applications. Within this work, what is common these episodes were excluded from tests.

Detailed listing of possible cases was presented here only to imagine the complexity of cardiac function. The relevant QRS complexes forms were shown in figure 5.

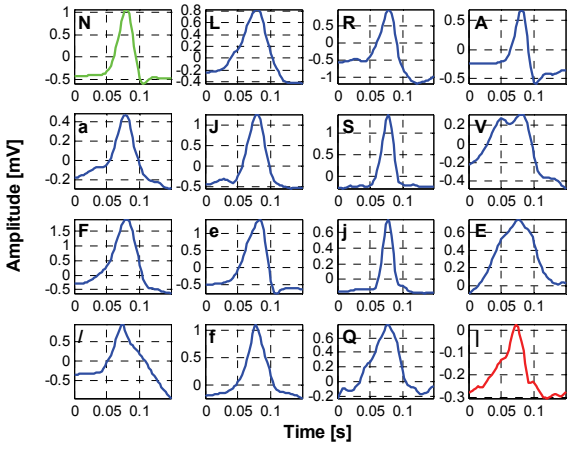

Fig. 5. Different types of beats [4].

Annotation of ECG signal includes also the type of the rhythm and some technical aspects of the recording itself as i.e. noise content in the part of the signal.

As it can be seen in the figure 5. QRS complex form is of a wide variability in terms of amplitude and time (frequency as well) parameters. Meaningful differences can be observed especially when comparing premature ventricular contraction (V) and ventricular escape beat (E) to normal beat (N).

The reference set of signals contains totally *TB* = 109492 QRS complexes (*TB* - *Total number of Beats*). There are different variants of tested algorithm detections in the evaluation procedure:

- there is only one QRS complex detected position in the defined neighborhood of the reference QRS complex position - detection is *true positive* - *TP*,
- there is more than one QRS complex detected position in the defined neighborhood of the reference QRS complex position - detection is *false positive* - *FP*,
- there is no QRS complex detected position in the defined neighborhood of the reference QRS complex position - detection is *false negative* - *FN*,
- there is even one QRS complex detected position outside the defined neighborhood of the reference QRS complex position - detection is *false positive* - *FP*.

According to the recommendations [8], based on the QRS complex detection results there are essential parameters of the QRS complex detection algorithm. These are:

- Sensitivity

(2) $$Se = \frac{TP}{TP + FN}$$

- Positive predictivity

(3) $$P^{+} = \frac{TP}{TP + FP}$$

and additionally:

- Error Rate

(4) $$ER = \frac{FP + FN}{TB}$$

- Reliability

(5) $$Re = 1 - ER = \frac{TB - FP - FN}{TB}$$

- Specificity

(6) $$Sp = \frac{TB - FP}{TB}$$

Respecting the above, there are *FN* = 140 and *FP* = 83 detections of the proposed algorithm, what makes the total error rate (*ER*) equal 0.20 % (tested on the complete set of signals included in the reference database [4] and calculated according to [8]). The relevant value of the original algorithm [6] equals 0.17 % (See Tab. 1 for details). The parameter makes both solution comparable. The advantage of the discussed solution is that maximum error rate for the particular signal from the reference set does not exceed 1.14 %, while respective, maximum value characterising reference algorithm equals 1.59 %.

Table 1. Comparison of the proposed and foundation algorithms.

Algorithm	*Se* [%]	P^{+} [%]	*ER* [%]	*Re* [%]	*Sp* [%]
Li *et al.* [6]	99,89	99,94	0,17	99,83	99,94
Presented solution [1,2,3]	99,87	99,92	0,20	99,80	99,92

There is a detailed presentation of *FN* detection for different types of QRS complex given in table 2.

Most *FN* detection can be observed for normal beats (N). There is no surprise as the total number of this QRS complex type accounts for over 68 % of the total number of beats (*TB*) included in the database [4]. What is more over 87 % of the false negative detected normal beats are localised in the noisy portions of the tested signals. As far as premature ventricular contractions (V) and aberrated atrial premature beats (a) are concerned one must notice that almost all of them are not distorted by the noise, but both forms differ significantly from the normal QRS complexes: (V) type is characterised by the longer duration time and lower slope and (a) type describes much more smaller amplitude (Fig. 5). It is worth adding that only less than 8% of the isolated QRS like artefacts (red plotted QRS, symbol I in the Fig. 5) were detected as real QRS complexes (See Tab. 2).

Table 2. The proposed algorithm *FN* detections for different types of QRS complex. FN_1 (FP_1) - value referred to the number of specified beat type; FN_2 (FP_2) - value referred to total number of false negative detections *FN* (*FP*).

Beat type	Number of beats	*FN*	FN_1 [%]	FN_2 [%]
N	74992	62	0,08	44,29
L	8071	3	0,04	2,14
R	7259	0	0,00	0
V	7080	49	0,69	35
/	7026	2	0,03	1,43
A	2543	1	0,04	0,71
f	982	0	0,00	0
F	801	2	0,25	1,43
j	229	0	0,00	0
a	132	18	13,64	12,86
E	106	0	0,00	0
J	83	0	0,00	0
Q	30	3	10,00	2,14
e	16	0	0,00	0
S	2	0	0,00	0
Total	109352	140	0,128	100
|	131	17(*FP*)	13(FP_1)	7,62(FP_2)

Table 3. The proposed algorithm false detections for different types of rhythms present in [4]. FN_1, FP_1 - values referred to the total number of beats (*TB*); FN_2, FP_2 - values referred to the total number of false detections *FN or FP* respectively.

Type of rhythm	*FN*	FN_1 [%]	FN_2 [%]	*FP*	FP_1 [%]	FP_2 [%]
Atrial bigeminy	0	0,000	0,000	0	0,000	0,000
Atrial fibrillation	27	0,025	19,286	11	0,010	13,253
Atrial flutter	5	0,005	3,571	8	0,007	9,639
Ventricular bigeminy	9	0,008	6,429	3	0,003	3,614
2° heart block	1	0,001	0,714	0	0,000	0,000
Idioventricular rhythm	0	0,000	0,000	1	0,001	1,205
Normal sinus rhythm	83	0,076	59,286	46	0,042	55,422
Nodal (A-V junctional) rhythm	0	0,000	0,000	1	0,001	1,205
Paced rhythm	5	0,005	3,571	3	0,003	3,614
Pre-excitation (WPW)	0	0,000	0,000	1	0,001	1,205
Sinus bradycardia	0	0,000	0,000	8	0,007	9,639
Supraventricular tachyarrhythmia	0	0,000	0,000	1	0,001	1,205
Ventricular trigeminy	2	0,002	1,429	0	0,000	0,000
Ventricular flutter	Not included in the test procedure					
Ventricular tachycardia	8	0,007	5,714	0	0,000	0,000
Total	140	0,128	100,000	83	0,076	100,000

In turn, there is a detailed presentation of the proposed algorithm *FN* and *FP* detections for different types of rhythms [4] shown in table 3. Similarly, normal sinus rhythm for which the fundamental representative is the normal beat (N) represents the highest level of false detections. Reasons for that fact are analogous to the described above during the normal beat discussion. Other rhythms characterised by the higher false detection rates are described by the considerably variable instant R-R interval. This covers: atrial fibrillation, atrial flutter, ventricular bigeminy, sinus bradycardia and ventricular tachycardia.

The other factor increasing false detections is variability of the adjacent QRS complexes amplitudes. This is common during ventricular tachycardia rhythm episodes present in the reference database [4]. These two factors together with noise present in the signals reveal weaknesses of the presented and evaluated algorithm.

Finally, there is a summary concerning signal quality (noisy periods) presented in table 4.

Table 4. The proposed algorithm false detection rate at the presence of low signal quality. FN_1, FP_1 - values referred to the total number of beats (*TB*); FN_2 ,FP_2 - values referred to the total number of false detections *FN or FP* respectively.

	FN	FN_1 [%]	FN_2 [%]	*FP*	FP_1 [%]	FP_2 [%]
Clean ECG signal	71	0,065	50,71	19	0,017	22,89
Noisy ECG signal	69	0,063	49,29	56	0,051	67,47
Unreadable ECG signal	0	0	0	8	0,007	9,64
Total	140	0,128	100,00	83	0,076	100,00

One can see that the signal quality (noise content) does not rather affect false negative (*FN*) detections of the proposed algorithm. On the contrary, algorithm seems to be noise sensitive, as the *FP* parameter rises significantly (Tab. 4) during noisy signal periods. Especially, during noisy, unreadable test periods additional *FP* appear.

Conclusions

Despite the fact that detailed analysis of false detections variables as the function of the parameters described in the paper is very complex and complicated it can bring helpful pointers in the research focused on rise of the reliability of the developed algorithm. In many cases it turns out that algorithm is not enough robust to noise. This problem can probably be solved by the implementation of some adaptive techniques into the wavelet transform based detection algorithm. Also initial signal filtering preceding the principal analysis could be justified. These methods are both supposed to be more effective than standard approach in rejecting signal episodes with significant content of disturbances. This takes into account high frequency interferences as well as “slow” baseline wanders. Further research should also be focused on analysis of the algorithm working parameters at the presence of rapid amplitudes changes of adjacent QRS complexes and also at the presence of high variability of R-R intervals in the analysed signal. This can involve redefinition of the threshold function which currently resembles a discrete, step down function. Further experiments can also take advantage of the curve of action potential of a heart muscle to model a more sophisticated threshold function.

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