Faculty of Electrical Engineering, Warsaw University of Technology, Koszykowa 75 Str., Warsaw, Poland

Introduction to wavelet based adaptive techniques in QRS complex analysis procedures

Streszczenie. W artykule przedstawione jest wprowadzenie do zagadnienia automatycznej i adaptacyjnej detekcji oraz analizy zespołów QRS w zapisach elektrokardiograficznych. W przeprowadzonych badaniach stosowano algorytmy, w których wykorzystano transformacje falkowe. Głównym celem opisanych badań jest opracowanie wiarygodnej procedury detekcji i opisu zespołów QRS prawidłowych oraz anormalnych. Wśród tych drugich skupiono się na zespołach pochodzenia komorowego. (Podstawy adaptacyjnych technik falkowych w zastosowaniu do detekcji i analizy zespołów QRS)

Abstract. The article discusses the problem of the automatic QRS complex detection in the electrocardiography signals. Among other approaches the wavelet based algorithms are the ones of the most promising outcomes. Authors propose introduction of elements of adaptive techniques to the original scheme. The main aim is to achieve reliable detection and analysis procedure for different morphologies of QRS complexes both normal and dysfunctional cases, with the main focus on ventricular arrhythmias.

Słowa kluczowe: Przekształcenie falkowe, detekcja zespołów QRS, Elektrokardiografia, Przetwarzanie sygnałów. **Keywords**: Wavelet Transform, QRS Detection, Electrocardiography, Signal Processing.

doi:10.12915/pe.2014.06.47

Introduction

Automatic QRS complex detection task is the well known problem in the computer aided electrocardiography signal analysis. There are many different solutions of the problem discussed in the literature. The wavelet transform is one of the mathematical apparatus that produce still very promising results of a high accuracy. It is valuable property because of an object character (human being) and the importance of diagnostics carried out by physicians. It is a very important requirement to have an accurate diagnosis describing condition of a patient.

Background

Continuous Wavelet Transform (CWT) can be described by formula (1).

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

$$= \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{s}} \psi^* \left(\frac{t-u}{s}\right) dt = f(t) * \overline{\psi}_{u,s}(t)$$

where ψ is a wavelet function; f is an analysed function; t is a time variable, s and u are dilation and translation coefficients respectively. Parameter s domain is commonly narrowed down to set of 2^j where j is a scale factor. This operation makes Dyadic Wavelet Transform (DWT) which is less redundant and is characterised by the computation process much faster, what is an essential advantage. However for the purpose of this article, CWT is used as it still preserve detailed background for the research and experiments.



Fig. 1. Different types of beats.

From (1) one can see that the results depend on the wavelet used ($\psi_{u,s}$). The quadratic spline wavelet is commonly used in the analysis of electrocardiography signals. It assures good frequency parameters coincidence of general QRS complex and wavelet transform coefficients across characteristic scales. In fact QRS complex can posture heterogonous shapes according to many different arrhythmias (Fig. 1). Especially notable difference exists between normal shapes of QRS (N in Fig. 1) and ventricular shapes of QRS complexes (V in Fig. 1). The difference exists both in time and amplitude. Therefore one should expect different WT coefficient distributions. This fact is proved by the results presented in the Fig. 2. Coefficients characteristic for normal QRS complexes differ from ventricular QRS complexes both in terms of their amplitude and scale subbands.



Fig. 2. CWT of different beat types. Normal sinus rhythm on the left. Premature ventricular contraction on the right.

Proposed solution

There are two fields of investigations, carried out by Authors independently. The first one relays on the wavelet adopting to QRS complexes characteristic for different subject and for different arrhythmias. By means of parallel computations based on different wavelets it is easier to obtain robust, reliable results and also to distinguish probable arrhythmias that can be present in the signal. The second field of research, mentioned above concerns the dynamic selection of coefficient scales taken to the diagnostic process. As it is presented in the Fig. 2. different set of scales preserve information on particular QRS complex properties. Robust algorithm for selecting set of scales narrowed down to characteristics of the QRS complexes reduces computational complexity making it easier to apply in the analysis procedure.

The two research fields mentioned above can be combined together as different wavelet shapes result in different frequency spectra of relevant digital filters. For the purpose of the paper they are discussed separately.

Results

The starting point of proposed analysis was chosen naturally by selecting original Quadratic Spline wavelet as a reference one in the research carried out. Essential experiments involved QRS complexes of type N and V. For this reason there were two appropriate wavelets prepared, corresponding to the N-type and V-type QRS complexes respectively (normal beat - N and ventricular contraction - V in Fig. 1). Based on the MIT-BIH Arrhythmia database [4], QRS complexes of types N and V were extracted separately. Separate sets of these two different QRS complex morphologies were used at first to determine relevant, representative average complexes. In turn these shapes of QRS complexes formed the basis of lowpass digital FIR filters set used in the wavelet decomposition algorithm. The complete process of filter coefficients computations consists of: QRS complexes extraction from the ECG recording (N-type and V-type independently), QRS averaging (mentioned above), symmetrisation of QRS average shape, decimation stage and final normalisation of the obtained coefficients. There were different decimation operations used during the research. The first decimation process was performed in the way that made the obtained FIR filters lengths equal to the original quadratic spline wavelet filters. One of the reasons of the action was the verification and possibility of comparison the "own" (Authors') wavelets to the original one. The decimation process was repeated, and performed in different conditions this time to achieve the frequency spectra moved towards the lower frequency bands. This can appear useful as there is a meaningful difference between the frequency spectrum of normal QRS complex (type N) and ventricular QRS complex (type V) [1,2,3]. Frequency spectrum of the latter QRS type is moved toward lower values of frequency. Different morphologies of the QRS complexes prompt both to use different filters (in terms of their frequency properties: pass band and cut-off frequencies) and analysis at different scales set of the wavelet transform coefficients. Brief results representing several representative cases are presented in the following figures (no. 3 to no. 7).



Fig. 3. Sample of an N-type QRS complex (region of the 250 sample) in the ECG recording no. 106 from MIT-BIH database (bottom subplot) together with wavelet transforms.

Each time the bottom subplot represents a sample of ECG signal. The middle subplot represents wavelet transform calculated for the original Quadratic Spline wavelet. The top subplot represents the wavelet transform calculated for the "own" wavelet, different for respective case N or V QRS type). Values in the brackets at the end of relevant figure titles preserve information regarding the length of base FIR filters used in the transforms. Lighter shades in the transforms pictures represent higher value of coefficients.



Fig. 4. Sample of an N-type QRS complex (region of the 140 sample) in the ECG recording no. 116 from MIT-BIH database (bottom subplot) together with wavelet transforms.

Figure no. 3 contains representative comparison of the original Quadratic Spline wavelet transform to the N-type QRS complex based own (Authors') wavelet. In this case the lengths of filters used in both transforms were exactly the same. Results are very interesting as the result transforms are almost identical. This is an additional, fresh proof of the Quadratic Spline wavelet adequateness in the ECG signal wavelet analysis. There is only one, above example presented in the article but it illustrates general phenomena observed during the research.



Fig. 5. Sample of an V-type QRS complex (region of the 350 sample) in the ECG recording no. 208 from MIT-BIH database (bottom subplot) together with wavelet transforms.

Figures no. 4 and no. 5 contain examples of comparison of V-type QRS complex wavelet transforms calculated with original quadratic spline and Authors' wavelet based on averaged QRS complex of type V. This time there are more visible differences between the results. As expected the area of the highest value coefficients (representing exact Vtype QRS complex wavelet transform) is significantly narrowed down and moved toward lower scale indexes for the averaged V-type QRS complex wavelet. This is potentially important property as QRS detection and identification algorithm would require less data set to operate.





Figures no. 6 and no. 7 present the second field of Authors' investigations which is based on different decimation factor. This relatively easy procedure let the ECG signal analysis algorithm developers model different and what is more important desired frequency spectra of the wavelet scales used in the transformation process. Comparison of wavelet transforms for a single QRS complex of type N, computed with a use of original Quadratic Spline wavelet and type-N QRS averaged wavelet is presented in the figure no. 6. Analogous comparison this time for a single QRS complex of type V is presented in the figure no. 7. It can be clearly seen in both examples that transforms computed with a use of averaged (Authors') wavelets give coefficients "squeezed" toward lower scale indexes. It is natural because of the fact that the base filter lengths of the Authors' averaged wavelets are



Fig. 7. Sample of an N-type QRS complex (region of the 250 sample) in the ECG recording no. 106 from MIT-BIH database (bottom subplot) together with wavelet transforms.

twice the length of the original wavelet what implicitly move their frequency spectra toward lower bands. In fact the modification of the wavelet decimation stage is an easy way of shifting resultant frequency spectra for the scales used in the wavelet transform.





Fig. 8. Sample of an V-type QRS complex (region of the 350 sample) in the ECG recording no. 208 from MIT-BIH database (bottom subplot) together with wavelet transforms.

Conclusions

Examples presented in the paper illustrate an approach to the adaptive wavelet transforms. This involves both online wavelet modification based on the signal being analysed and also on-line scale set selection in order to determine the most representative group for the analysis procedure. Presented examples preserve one more potential advantage already mentioned above. 'Compressed" and moved down to the lower scale indexes, wavelet coefficients define the narrowed set of data that is to be analysed by the algorithm. And, the smaller amount of data to analyse, the faster computation process. Of course this thesis must be verified upon computation comparison based on original and modified (Authors') wavelet. At the moment it can be recapitulated that obtained results are promising. Authors would like to continue study on wavelet transform ECG analysis algorithm development and to introduce into it on-line adaptive solutions making the final effect more reliable and robust.

REFERENCES

- Jóško A., Evaluation of the QRS complex wavelet based detection algorithm, *Electrical Review No. 5/2011*, Przeglad Elektrotechniczny Nr. 5/2011.
- [2] Figoń P., Irzmański P., Jóśko A., Rak R., Staroszczyk Z., QRS detector approach for on-line purposes, *Electrical Review No.* 4/2013, Przegląd Elektrotechniczny, Nr. 4/2013.
- [3] Figoń P., Irzmański P., Jóśko A., ECG signal quality improvement techniques, *Electrical Review No. 4/2013*, Przegląd Elektrotechniczny, Nr. 4/2013.
- [4] MIT-BIH Arrhythmia Database, Third Edition, May (1997)

Authors: Paweł IRZMAŃSKI M.Sc., Warsaw University of Technology, Institute of Theory of Electrical Engineering, Measurement and Information Systems, 75 Koszykowa Str., 00-662 Warsaw, E-mail: <u>pawel.irzmanski@ee.pw.edu.pl</u>

Adam JÓŚKO PhD., Warsaw University of Technology, Institute of Theory of Electrical Engineering, Measurement and Information Systems, 75 Koszykowa Str., 00-662 Warsaw, E-mail: adam.josko@ee.pw.edu.pl