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Conference Paper · September 2023

DOI: 10.1109/IDAACS58523.2023.10348849

Anatoliy Sachenko
West Ukrainian National University

Volkova Nataliya
Odessa National Polytechnic University

Bohdan Rusyn
G.V. Karpenko Physical-Mechanical Institute

Piotr Pikiewicz
Silesian University of Technology

The 12th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications
September 7-9, 2023, Dortmund, Germany

Increasing the Accuracy of Determining RR Intervals of ECG using Wavelet Transform

Galina Shcherbakova [1], Svetlana Antoshchuk [1], Anatoliy Sachenko [2,4], Nataliia Volkova [1], Bohdan Rusyn [3,4], Sergey Rippa [5]

[1] Odessa National Polytechnic University, 65044 Odessa, Ukraine; galina_sherbakova@op.edu.ua, asg@op.edu.ua, volkova.np@op.edu.ua

[2] West Ukrainian National University, Ternopil, Ukraine, as@wunu.edu.ua

[3] Karpenko Physico-Mechanical Institute of the NAS of Ukraine, Lviv, Ukraine, rusyn@ipm.lviv.ua

[4] Kazimierz Pulaski University of Technology and Humanities, Radom, 26-600, Poland, b.rusyn.prof@gmail.com

[5] Kyiv National Economic University, 03680 Kyiv, Ukraine, rippa_serg@ukr.net

***Abstract*—The paper presents a method for determining the coordinates of the extremum of non-stationary periodic signals based on optimization with wavelet transform. The procedures for evaluating the determination of the coordinates of R waves and the intervals between them for electrocardiograms based on the search with the Haar wavelet function are given. The error in estimating the duration of intervals in the studied set of signals under conditions of increasing noise levels is studied. The influence of the length of the support of the Haar wavelet function and the step size on the speed of the search is estimated.**

Keywords—optimization; wavelet transform; electrocardiogram; arrhythmia; diagnostics

I. INTRODUCTION AND RELATED WORK

The modern level of data processing, for example, in telemedicine, often requires the analysis of non-stationary periodic signals. Electrocardiograms (ECGs) are an example of such signals. As a rule, three stages of data processing are carried out when diagnosing cardiovascular diseases using ECGs: pre-processing, identification (feature extraction), and classification [1].

In this case, often the measurement of such signals does not allow to get rid of noise. These noises arise during the registration of signals and during the transmission of data over communication lines [2-6]. The pre-processing step aims to eliminate such noises. To eliminate these features of the ECG signal, low-pass and high-pass filters and/or wavelet processing [1] are often used. ECG signals have complex time-frequency characteristics with high-frequency and low-frequency components. Therefore, the estimation of the parameters of such signals based on the analysis of only frequency characteristics with overlapping spectra [7, 8] of the useful ECG signal and noise can lead to a decrease in the reliability of diagnostics [6, 9].

According to the authors [1, 10] and in accordance with the protocols of medical research, during identification, signs are distinguished that can distinguish the features of the studied diseases. Due to the high variability of heart rate in a number of diseases, it is often difficult to obtain large data sets even from the same patient [1]. In addition, due to the relevance of the problem being solved, there are a large number of methods aimed at automating the identification procedure. Among these identification methods, three groups can be distinguished: methods that highlight the signs of changes in the amplitude and frequency of heartbeats over time, methods that highlight the spectral parameters of ECG signals, and methods that enables to determine both the temporal and frequency characteristics of the ECG signal - wavelet processing methods.

Due to the variety of methods, an important task is to reduce the dimension of the feature set, which allows reducing computational costs and increasing performance at the classification stage [11, 12, 13]. So, for example, at this stage, such methods of feature selection are used as methods aimed at recursively reducing the set of features; genetic and swarm algorithms [1, 13, 14], methods of dispersion analysis [1, 13, 14].

Reducing the volume of processed data to the identification stage allows the use of wavelet transforms (WT) for ECG analysis [4, 7, 8, 15]. With this analysis, the signal under study is decomposed into a set of wavelet functions (WF) [16]. These functions take into account the time shift and changes in the scale of the original WF [4]. Therefore, processing with WT allows taking into account the temporal and frequency features of the signal, obtaining a set of coefficients for subsequent processing [17].

Due to the complexity of the tasks the methods of processing ECG at the present stage are diverse [18]. Thus, there are known approaches to ECG analysis based on chaos theory, a combination of statistical, geometric and non-linear signs of heart rate variability, RPCA - recursive principal component analysis, SPSA - Simultaneous perturbation stochastic approximation method, FDBT - First Derivative Based Technique, SDBT - Second Derivative Based Technique, method based on the Hilbert transform and others [1]. Some of these methods, for example, methods based on the estimation of the first and second derivatives in the conditions of estimating the parameters of a non-stationary ECG signal with many extremes, may have low noise immunity and/or increased error.

A number of authors use one of the processing levels with WT as a classification vector for subsequent classification [17]. Another approach involves the evaluation of the statistical characteristics of the ECG signal after processing with WT [12]. This approach uses these statistical characteristics as a classification vector in diagnostics. However, for example, for the diagnosis of various types of arrhythmias, the analysis of large amounts of data is required. Therefore, both approaches require significant computation time [19]. With high requirements for efficiency [5] reduce the dimension of the classification vector by determining the characteristic features of the QRS fragments of the ECG (fig.1). It should also be noted that the dimension of the feature vector varies during identification for different diseases [10]. So, for example, a number of authors the levels of processing with the WF and the scales of the wavelet functions are determined [20]. This approach in the analysis of long-term ECG, for example, when using the Holter monitor [7], allows you to reduce the size of the initial data set (fig.2, a) during processing (fig.2, b).

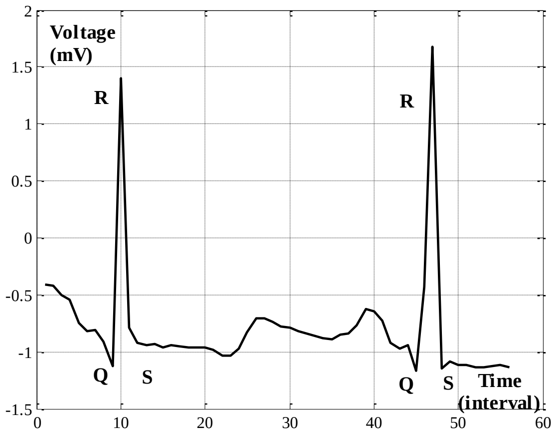


Figure 1. A standard ECG waveform with QRS complex

To search for the extremum of noisy polymodal functions, an optimization method was developed using the WT, the noise immunity of which was proved by the authors [21]. The authors proposed a method for searching for extrema of periodic signals, using a number of stages of this method [21] to determine the intervals between R ECG waves. In this work, only the stages of signal processing using the wavelet function - the Haar WF [14, 21] were used, the parameters of the method were selected, and their influence on the speed of the procedure for estimating the coordinates of extremes was evaluated.

II. Method of Searching the Coordinates of Extrema for Periodic Signals

As a result of studies of noise immunity, convergence rate, and error in [21], to estimate the direction of the search for the extremum coordinate in (2), it is necessary to use symmetric and non-stationary wavelet functions - the Haar WF [19, 21, 22]. In this case, the extremum coordinate is estimated according to the iterative scheme:

$$c[n] = c[n-1] - \gamma[n] WT_k (Q(x[n], c[n-1])), \quad (1)$$

where $\gamma[n]$ is the step; n is the iteration number; k is the start number; WT_k determines the direction of movement towards the extremum and is calculated according to:

$$WT_k (Q(x[n], c[n-1])) = \{G_{1k}, G_{2k}, \dots, G_{Nk}\}, \quad (2)$$

G_{jk} is the result of processing j-th variable:

$$G_{jk} = \frac{1}{s_k} \sum_{\substack{i=-\frac{s_k}{2} \\ i \neq 0}}^{\frac{s_k}{2}} Q(x[n], c_j + ia) \cdot \Psi_k(i) \quad (3)$$

s_k is the carrier length of the WF; a is the WF discretization step; $\Psi_k(i)$ is the Haar WF at the k-th start; $j = 1, \dots, N$ is the dimension of the parameter vector.

This approach makes it possible to determine the range of variation of the extremum coordinates [21] with δ_1 – error of searching for the optimum start (determined at the stage of a priori studies of the quality functional); δ_2 is the error in the search for the optimum of the applied problem. The search is performed with the following parameters: $c[0]$ – initial approximation to the optimum coordinate in the first period; $\gamma[1]$ - step; a is the WF discretization step; s_1 is the WF carrier length of the first start $\Psi_1(i)$; Δ_s is the step of changing the length of the WF carrier $\Psi_1(i)$ when determining the range of extremum coordinates; A_1 is the value of the minimum height of the recorded extremum; ΔR is the initial approximation to the value of the duration of the interval between the recorded extrema.

When searching for the R wave, the direction of the search is estimated according to (2) at the point of approach to the optimum coordinate for the start k. To do this, we use a weighted sum with the Haar WF with s_1 (at point $c[0]$ at $n=1$). The influence of the carrier length of this WF $\Psi_1(i)$ on the performance in the analysis of the ECG and is investigated in the work. At this stage, the sign of the estimate according to (3) is checked $G_{jk}=\frac{1}{s_k}\sum_{\substack{i=-\frac{s_k}{2}\\ i\neq 0}}^{\frac{s_k}{2}} Q(x[n],c_j+ia)\cdot\Psi_k(i)$. Further, based on the known property of the WT to change sign when passing through the optimum, at this stage the range of change of the extremum coordinates is determined as $c[n-1]\leq c^* < c[n]$. Next, a search is made for the ranges of coordinates of the optimum $Q(x,c)$ according to (1) at k until the end of the data set under study.

To reduce the amount of analysis data, the WT of the analyzed ECG signal was carried out in the work. To reduce the noise level of the ECG signal analyzed during the search for R waves, the Daubechies WF1 is used [16, 23]. Determination of the spatial coordinates of R waves by searching for the coordinates of the extrema of periodic signals using the developed method. Signals from the MIT/BIH Arrhythmia Database [20] were studied as such signals. For the sequence (Fig. 2, b), the coordinates of the and the intervals between them are determined.

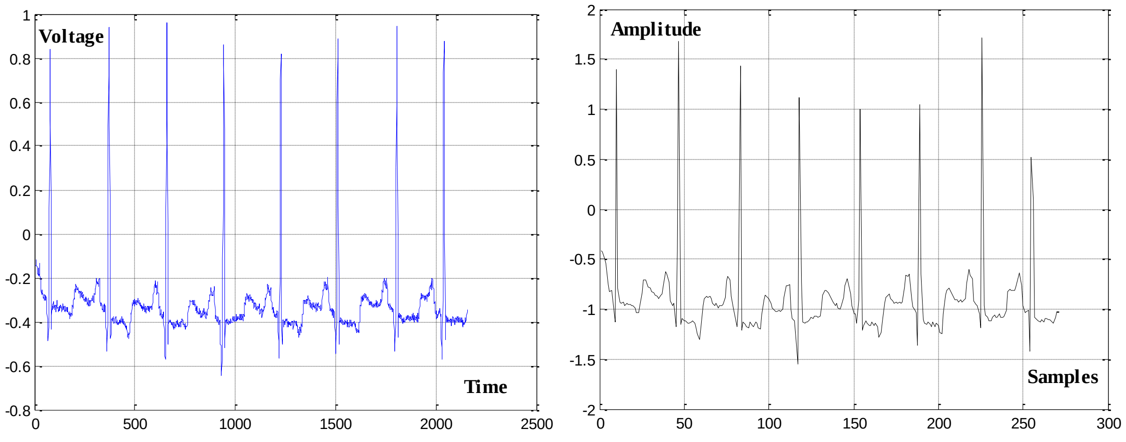
III. CASE STUDY

The work evaluated the effect of changing the carrier length s_k for speed. After the change in the sign of the WT when passing through the optimum, the range of change in the coordinates of the extremum is determined as $c[n-1]\leq c^* < c[n]$. Next, the length of the WF carrier is determined to search for the next extremum in the data set s_k. Meaning s_k during the study, it changes from 20 to 32. At the same time, due to the integral nature of the Haar WT, with an increase in the length of the WF carrier, the coordinate of the next search step is more or less shifted to the extremum of the next period. So, when changing the studied values s_k from 20 to 32, and the size $\gamma=1.7$ the search time for the coordinates of the R waves changed by less than 10% (at the initial value $s_1=3$). We also assessed the influence of the step size $\gamma[n]$ on the evaluation speed. So (at the initial value $s_1=5$) and change γ from 1.4 to 2.0, the time to determine the coordinates of the first 7 extrema (Fig. 2b) increased by 5%. Relative errors in the determination were: for the coordinates of R waves no more than 1.4%, for the duration of the intervals between them is no more than 2.4%. In the study of noise immunity, the relative error in determining the duration of the intervals is less than 4% with a signal-to-noise ratio in amplitude of 20 ... 10.

These results allow us to recommend the developed method for use in information technologies for telemedicine, with an increase in the noise level in ECG signals.

IV. CONCLUSION

The paper presents a method for determining the coordinates of the extremum of non-stationary periodic signals based on optimization with wavelet transform. The procedures for evaluating of the coordinates of R waves and the intervals between them for electrocardiograms based on the search with the Haar WF are given. The error in estimating the duration of intervals in the studied set of signals under conditions of increasing noise levels is studied. The relative error in the duration of the intervals between R waves was less than 4% with an amplitude



a, input ECG signal   b, coefficient WF Daubechi 1

Figure 2. ECG signal at different stage of analysis (a) – input ECG signal, b) – coefficient WF Daubechi

signal-to-noise ratio of up to 10. For the well-known Pan-Tompkins algorithm, this value is at least 5% [24, 25]. The relative error for the coordinates of R waves is not more than 1.4%. The performance evaluation showed that when the studied values s_k changed from 20 to 32, and the value $\gamma = 1.7$, the search time for the coordinates of R waves changed by less than 10% (with the initial value $s_1 = 3$). At the same time, an assessment of the influence of the step size $\gamma[n]$ on the speed of searching for the coordinates of R waves showed that when γ changes from 1.4 to 2.0, the time to determine the coordinates of the first 7 extrema (Fig. 2b) increased by 5%.

Thus, we can conclude that the developed method for determining the coordinates of extrema has an error and noise immunity that meet the requirements of this applied problem.

References

[1] Atamanyuk, I., et al. Computational method of the cardiovascular diseases classification based on a generalized nonlinear canonical decomposition of random sequences. Scientific Reports 13, 59 (2023). https://doi.org/10.1038/s41598-022-27318-0

[2] W. Liu, S. Li, M. Chen, Y. Fang, L. Cha and Z. Wang, "Fault Diagnosis for Attitude Sensors Based on Analytical Redundancy and Wavelet Transform," *2020 Chinese Automation Congress (CAC)*, Shanghai, China, 2020, pp. 6471-6476, doi: 10.1109/CAC51589.2020.9327370.

[3] Prashar, N., Sood, M., & Jain, S. (2021). Design and implementation of a robust noise removal system in ECG signals using dual-tree complex wavelet transform. *Biomedical signal processing and control*, *63*, 102212. https://doi.org/10.1016/j.bspc.2020.102212.

[4] Kumar, M., Pachori, R. B., & Acharya, U. R. (2017). Automated diagnosis of myocardial infarction ECG signals using sample entropy in flexible analytic wavelet transform framework. *Entropy*, *19*(9), 488. https://doi.org/10.3390/e19090488.

[5] Ferreira Jr, M., & Zanesco, A. (2016). Heart rate variability as important approach for assessment autonomic modulation. *Motriz: Revista de Educação Física*, *22*, 3-8. https://doi.org/10.1590/S1980-65742016000200001.

[6] Sundararaj, V. (2019). Optimised denoising scheme via opposition-based self-adaptive learning PSO algorithm for wavelet-based ECG signal noise reduction. International Journal of Biomedical Engineering and Technology, 31(4), 325-345. https://doi.org/10.1504/IJBET.2019.103242

[7] Cesari, M., Mehlsen, J., Mehlsen, A. B., & Sorensen, H. B. D. (2017). A new wavelet-based ECG delineator for the evaluation of the ventricular innervation. *IEEE journal of translational engineering in health and medicine*, *5*, 1-15. 2017, Jul 4;5:2000215. doi: 10.1109/JTEHM.2017.2722998.

[8] Jacob, Dr.Vinodkumar and K. N. Ramachandran Nair. “Automation of ECG heart beat detection using Morfological filtering and Daubechies wavelet transform”, *International organization of Scientific Research Journal of Engineering (IOSRJEN),* vol. 04, issue 12, pp. 53 – 58, 2014. DOI:10.9790/3021-041215358

[9] M. Omar, A. Mohamed. “Evaluation of Morphological Characterization of the Long-Record ECG Signal and its HRV for Congestive Heart Failure”, *The Online Journal on Computer and Information Technology (OJCSIT)*, vol. 2, no 1, pp. 107 – 110, 2011

[10] Shebanin, V., et al. Canonical mathematical model and information technology for cardio-vascular diseases diagnostics. 2017 14th International Conference The Experience of Designing and Application of CAD Systems in Microelectronics, CADSM 2017 - Proceedings Open Access, 2017, pp. 438-440, DOI: 10.1109/CADSM.2017.7916170

[11] M. Dyvak and A. Pukas, "Criterion of Design of Experiments for Tasks of Decision Support Interval Model Creation," 2005 IEEE Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, Sofia, Bulgaria, 2005, pp. 495-497, doi: 10.1109/IDAACS.2005.283032.

[12] Gutierrez-Ojeda, J., Ponomaryov, V., Almaraz-Damian, J.-A., Reyes-Reyes, R., & Cruz-Ramos, C. (2023). ECG Arrhythmia Classification Using Recurrence Plot and ResNet-18. International Journal of Computing, 22(2), 140-148. https://doi.org/10.47839/ijc.22.2.3083

[13] N. Porplytsya, M. Dyvak, I. Spivak and I. Voytyuk, "Mathematical and algorithmic foundations for implementation of the method for structure identification of interval difference operator based on functioning of bee colony," The Experience of Designing and Application of CAD Systems in Microelectronics, Lviv, Ukraine, 2015, pp. 196-199, https://doi: 10.1109/CADSM.2015.7230834.

[14] Bhuvaneswari Amma, N. Cardiovascular disease prediction system using genetic algorithm and neural network. In *Proceedings of 2012 International Conference on Computing, Communication and Applications/* 1–5. https://doi.org/10.1109/ICCCA.2012.6179185

[15] Sinha, N. & Das, A. Automatic diagnosis of cardiac arrhythmias based on three stage feature fusion and classification model using DWT. *J. Biomed. Signal Process. Control* 62, 102066. https://doi.org/10.1016/j.bspc.2020.102066 (2020).

[16] I. Daubechies, “Ten Lectures on Wavelets”, CBMS-NSF Lecture Notes, no.61, 1992. Available from: https://jqichina.files.wordpress.com/2012/02/ten-lectures-of-waveletsefbc88e5b08fe6b3a2e58d81e8aeb2efbc891.pdf.

[17] Xie L, Li Z, Zhou Y, He Y, Zhu J. Computational Diagnostic Techniques for Electrocardiogram Signal Analysis. *Sensors (Basel).* 2020 Nov 5;20(21):6318. doi: 10.3390/s20216318.

[18] Gupta, V., Saxena, N. K., Kanungo, A. Gupta, A. & Kumar, P. (2022) A review of different ECG classification/detection techniques for improved medical applications. *Int. J. Syst. Assur. Eng. Manag.* 1–15. https://doi.org/10.1007/s13198-021-01548-3.

[19] Huan, W., Shcherbakova, G., Sachenko, A., Yan, L., Volkova, N., Rusyn, B., & Molga, A. (2023). Haar Wavelet-Based Classification Method for Visual Information Processing Systems. *Applied Sciences*, *13*(9), 5515. https://doi.org/10.3390/app13095515

[20] MIT/BIH Arrhytmia Database. Available from: http://physionet.org/physiobank/database/mitdb/. – Active link. – 15.04.23.

[21] G. Shcherbakova, Shi Hao-Su, V. Krylov, N. Bilous, S. Antoshchuk «Estimation of the Duration of RR-intervals of Electrocardiograms by Mean of Multi-start Optimization Based on Wavelet Transformation» *// IEEE* 9th *International Workshop on Intelligent Data Acquisition and Advanced Computing Systems*, 21-23 September 2017, Bucharest, Romania, 2017.

[22] R. Gonzales, R. Woods, *Digital image processing*. - Pearson education, Inc. Prentice Hall, 2002. – Available at: https://www.academia.edu/25992484/Digital_Image_Processing_Second_Edition – Active link. – 15.04.23.

[23] Mandala S, Pratiwi Wibowo AR, Adiwijaya, Suyanto, Zahid MSM, Rizal A. The Effects of Daubechies Wavelet Basis Function (DWBF) and Decomposition Level on the Performance of Artificial Intelligence-Based Atrial Fibrillation (AF) Detection Based on Electrocardiogram (ECG) Signals. *Applied Sciences*. 2023; 13(5):3036. https://doi.org/10.3390/app13053036

[24] J. Pan, W. Tompkins, "A Real-Time QRS Detection Algorithm," in *IEEE Transactions on Biomedical Engineering*, vol. BME-32, no. 3, pp. 230-236, 1985, doi: 10.1109/TBME.1985.325532.

[25] Sedghamiz H. (2014) "Matlab Implementation of Pan Tompkins ECG QRS detector"– Available at https://www.researchgate.net/publication/313673153 _Matlab_implementation_of Pan_Tompkins_ECG _QRS_detect – Active link. – 02.05.23.