eoss-conf.com

ISSUE №54

EUROPEAN OPEN SCIENCE SPACE

COLLECTION OF SCIENTIFIC PAPERS

3RD INTERNATIONAL SCIENTIFIC AND PRACTICAL CONFERENCE

MODERN PROBLEMS OF SCIENCE AND TECHNOLOGY

SEPTEMBER 22-24, 2025, TALLINN, ESTONIA

EUROPEAN OPEN SCIENCE SPACE

Proceedings of the 3rd International Scientific and Practical Conference

"Modern Problems of Science and Technology"

September 22-24, 2025

Tallinn, Estonia

Collection of Scientific Papers

Tallinn, 2025

залежить від тривалості роботи з різною величиною завантаження, від величини та складності перехідних режимів, від впливу зовнішніх аварійних режимів.

Для асинхронних електродвигунів з короткозамкнутою обмоткою ротора проводиться пряме включення в мережу, що викликає великі пускові струми з перегріванням статора і обмоток ротора. А тому, необхідний контроль стаціонарного навантаження, числа і тривалості кожного пуску.

Організація ремонту електрообладнання з урахуванням напрацювання дозволить підвищити його надійність за рахунок своєчасного виведення в ремонт функціональних складових з найбільш високою ймовірнісю відмови.

Список використаних джерел

1. Казак В.М., Доценко Б.І., Кузьмін В.П. та ін. Надійність та діагностика електрообладнання: навч. посібник. К. : НАУ, 2013. 280 с.
2. Яцун М. А. Експлуатація та діагностування електричних машин і апаратів. Львів: Львівська політехніка, 2010. 228 с.
3. Стребков О. А. Дослідження електромеханічних і теплових перехідних процесів при пуску асинхронних електродвигунів. Технологічний аудит і резерви виробництва. 2015. 6(26). С. 18-25.

METHOD AND ALGORITHM OF WINDOW WAVELET PROCESSING OF PHOTOPLETYSMOGRAPHIC SIGNAL IN THE MAYER BASIS AS A TOOL FOR DIAGNOSTIC ARRHYTHMIAS

Khvostivskyi Mykola
Ph.D., Associate Professor
Kirash Victoriia
Student
Khvostivska Liliia
Ph.D., Associate Professor
Karabinenko Yuliia
Student
Ternopil Ivan Puluj National Technical University, Ukraine

Cardiovascular diseases, in particular cardiac rhythm abnormalities, remain one of the leading causes of morbidity and mortality worldwide [1]. This necessitates the development of new methods of cardiac monitoring that can provide high accuracy and sensitivity in detecting both short-term and long-term abnormalities.

Photoplethysmography (PPG) or pulse signal is a promising non-invasive method that allows recording changes in peripheral vascular blood flow and obtaining information about heart rate, amplitude and time characteristics of pulse waves. Due to their availability and ease of registration, PPG signals are increasingly used in medical research and cardiac monitoring systems. However, their effectiveness largely depends on the applied methods and algorithms of digital processing.

Among the known methods of processing PPG signals for detecting heart rhythm anomalies (spectral [2-4], correlation [5], statistical [6-8], entropy [9-11], morphological [12-13], synphase/component [14], machine learning [15], deep learning [16, 17]), wavelet processing deserves special attention, which allows for simultaneous examination of the signal in the time and frequency domains. However, the classical wavelet approach has limitations in localizing fast rhythm changes. Therefore, window wavelet processing, which combines adaptive scaling of wavelets with sliding temporal segmentation of the signal, is particularly promising.

The PPG signal is recorded using an optical sensor that records changes in blood volume in the tissues. Due to the characteristics of the sensor and electronics, the signal often contains a constant offset (DC component) - a constant component that does not carry useful information about pulse activity. For this, it is necessary to perform pre-processing, in particular centering and amplitude normalization.

Centering of the PPG signal is implemented according to the expression:

$$x_c[n] = x[n] - \mu, \quad \mu = \frac{1}{N}\sum_{n=1}^{N} x[n]. \tag{1}$$

Normalization of the amplitude of the PPG signal is implemented according to the expression:

$$x_m[n] = \frac{x_c[n]}{\max(|x_c[n]|)}. \tag{2}$$

Thus, normalization ensures the stability of the algorithm, makes the processing results independent of sensory or individual characteristics of the signal, and allows for the correct identification of dominant frequencies and anomalies.

After centering and normalization, the PPG signal is subjected to bandpass filtering, which limits its frequency spectrum to physiologically significant components of the heart rate in the cardio range of 0.5–15 Hz. The bandpass filter passes only frequencies in a defined range [f_{low}, f_{high}] and suppresses frequencies outside it:

$$x_{bp}[n] = Bandpass(x_n[n], f_{low}, f_{high}), \tag{2}$$

where f_{low}=0,5 Гц і f_{high}=15 Гц.

Analysis of the PPG signal as a whole can hide short-term changes in heart rate. To overcome this problem, it is proposed to divide the signal into overlapping windows of length L_w and shift step L_s:

$$L_w = T_w f_d, \quad L_s = T_s f_d, \tag{3}$$

where T_w – time window length in seconds, T_s – shift step in seconds.

Then the k-th signal window is formed as:

$$x_k[n] = x[n + (k-1)L_s], \quad n = 0,\ldots,L_w - 1. \tag{4}$$

Therefore, the use of overlapping windows in processing the PPG signal provides local frequency estimation, overlapping for smooth transition, balance of accuracy and resolution, and stability of statistical estimates.

The PPG signal is non-stationary, i.e. its frequency characteristics change over time due to natural heart rate variability, motion artifacts, or changes in peripheral blood circulation. Traditional spectral methods, such as discrete or fast Fourier transforms, do not allow for simultaneous determination of frequency characteristics and their temporal evolution. In this case, the continuous wavelet transform is used, which is an effective method of local time-frequency analysis for each window $x_k[n]$ of the signals:

$$C(f,k)=\sum_{n=0}^{L_w-1} x_k[n]\psi\left(\frac{n}{f_d},f\right), \tag{5}$$

where $C(f,k)$ – complex wavelet transform coefficients, $\psi(t,f)$ – Meyer basis:

$$\hat{\psi}_{Meyer}(\omega)=\begin{cases}\frac{1}{\sqrt{2\pi}}\sin\left(\frac{\pi}{2}v\frac{3|\omega|}{2\tau}-1\right)e^{j\omega/2}, & \frac{2\pi}{3}\le|\omega|\le\frac{4\pi}{3}\\ \frac{1}{\sqrt{2\pi}}\sin\left(\frac{\pi}{2}v\frac{3|\omega|}{2\tau}-1\right)e^{j\omega/2}, & \frac{4\pi}{3}\le|\omega|\le\frac{8\pi}{3}\\ 0 & \textit{інакше}\end{cases}, \tag{6}$$

where $v(x)$ – smooth transition function:

$$v(x)=\begin{cases}0, & x\le 0\\ x, & 0<x<1\\ 1, & x\ge 1\end{cases}. \tag{7}$$

Time form:

$$\psi_{Meyer}(t)=\frac{1}{2\pi}\int_{-\infty}^{\infty}\hat{\psi}_{Meyer}(\omega)e^{j\omega t}d\omega. \tag{8}$$

Meyer wavelet allows to accurately distinguish the dominant frequency of heart rate oscillations (0.5-5 Hz). Smooth spectral shape minimizes the influence of high-frequency noise and trends. Complex waveform allows to determine local features of the signal in each window.

Calculating energy by frequencies in windowed wavelet processing of the PPG signal is a key step for isolating the dominant heart rate frequency in local signal segments according to the expression:

$$E(f,t_k)=\sum_{n=0}^{L_\omega-1}\left|C(f,t_k)\right|^2. \tag{9}$$

The maximum energy corresponds to the frequency at which the signal has the greatest contribution — that is, the dominant heart rate frequency in the cardio range

[0.5-5 Hz] (corresponds to the physiological limits of pulse rate (30-300 beats/min)), which is calculated according to the expression:

$$f_0(t_k) = \arg \max_{f \in [0.5,5]} E(f, t_k). \quad (10)$$

The dominant frequency $f_0(t_k)$ in each window allows us to estimate the local period of the heart rhythm $T(t_k) = 1/f_0(t_k)$.

Rhythm anomalies are determined based on physiologically justified local period boundaries:

$$T_{\min} \le T(t_k) \le T_{\max}, \quad T_{\min} = 0.6\,\text{сек}, \ T_{\max} = 1.2\,\text{сек} \quad (11)$$

Windows in which the local period falls outside this range are classified as anomalous. The algorithm for window wavelet processing of the PPG signal is shown in Fig. 1.

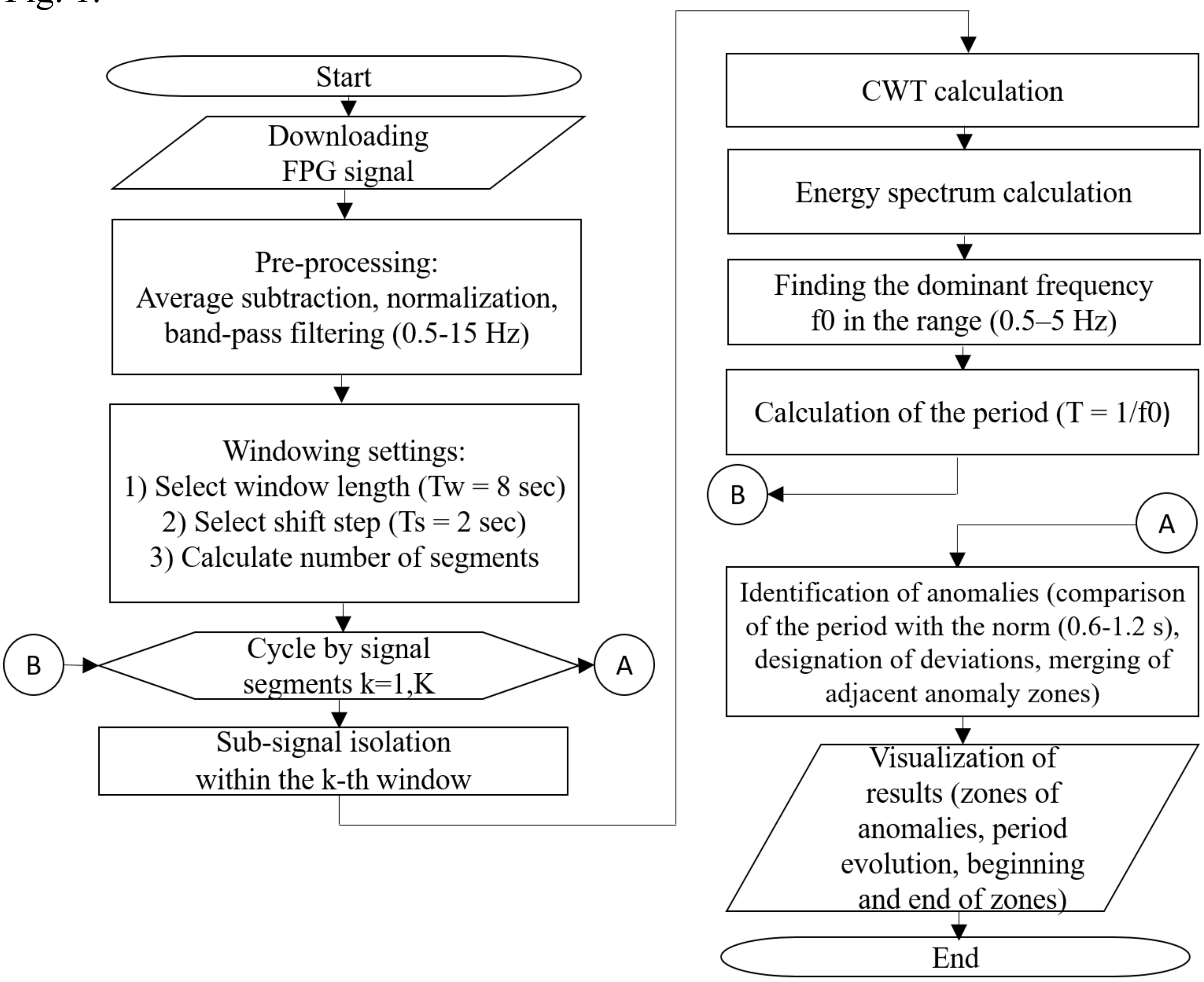

Fig. 1. Algorithm for window wavelet processing of a PPG signal

The proposed algorithm for window wavelet processing of the PPG signal involves pre-filtering, signal segmentation in overlapping windows, and the application of continuous wavelet transform in the Meyer basis to determine the dominant frequency and detect heart rate deviations from the norm. Its relevance lies in the possibility of accurate, non-invasive, and noise-resistant diagnosis of tachycardia and bradycardia in real time, which is especially important for medical monitoring systems.

References

1. World Health Organization. Newborn mortality [Internet]. Updated Mar 14, 2024. Available from: https://www.who.int.
2. Park J., Lee J., Oh J. Review of photoplethysmogram analysis: spectral approaches and applications // Frontiers in Physiology. – 2022. – Vol. 13. – P. 1–12. DOI: 10.3389/fphys.2022.123456.
3. Bereznyi I.V., Nakonechnyi A. Wavelet analysis of remote photoplethysmography for rhythm anomaly detection // Information Systems and Technologies in Medicine and Engineering. – 2025. – Vol. 29, №1. – P. 45–53.
4. Cheng Y., Zhang X., Li H. Continuous wavelet transform and deep learning for atrial fibrillation detection using PPG // Biomedical Signal Processing and Control. – 2021. – Vol. 68. – P. 102741. DOI: 10.1016/j.bspc.2021.102741.
5. Väliaho E.-S., Lipponen J.A., Kuoppa P., Martikainen T.J. et al. Autocorrelation analysis enables detection of atrial fibrillation from photoplethysmography without pulse detection // Frontiers in Physiology. – 2021. – Vol. 12. – P. 726451. DOI: 10.3389/fphys.2021.726451.
6. Tison G.H., Sanchez J.M., Ballinger B. et al. Passive detection of atrial fibrillation using a commercially available smartwatch // JAMA Cardiology. – 2018. – Vol. 3(5). – P. 409–416. DOI: 10.1001/jamacardio.2018.0136.
7. Paradkar N., Chowdhury S.R. Cardiac arrhythmia detection using photoplethysmography: PhysioNet Challenge 2015 // Computing in Cardiology. – 2015. – Vol. 42. – P. 273–276.
8. Park J., Lee S., Jeon M. Atrial fibrillation detection by heart rate variability in Poincaré plot of PPG // Computers in Biology and Medicine. – 2009. – Vol. 39(8). – P. 746–754. DOI: 10.1016/j.compbiomed.2009.06.006.
9. Bashar S.K., Han D., Hajeb-Mohammadalipour S. et al. Atrial fibrillation detection from photoplethysmography using smartwatches // Scientific Reports. – 2019. – Vol. 9. – P. 15054. DOI: 10.1038/s41598-019-50940-0.
10. Pereira T., Tran N., Gadhoumi K. et al. Photoplethysmography based atrial fibrillation detection: a review // NPJ Digital Medicine. – 2020. – Vol. 3(1). – P. 3. DOI: 10.1038/s41746-019-0207-9.
11. Lee W., Jung W., Lee Y. Atrial fibrillation detection using smartphone and entropy measures // Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). – 2012. – P. 1177–1180.
12. Charlton P.H., Bonnici T., Tarassenko L. et al. An integrative review of the photoplethysmogram: analysis and applications // Physiological Measurement. – 2022. – Vol. 43. – P. 05TR01. DOI: 10.1088/1361-6579/ac5f3d.
13. Li Q., Clifford G.D. Signal quality and data fusion for photoplethysmogram analysis using dynamic time warping // Physiological Measurement. – 2012. – Vol. 33(9). – P. 1491–1501. DOI: 10.1088/0967-3334/33/9/1491.
14. Хвостівська Л. В. Математична модель та методи аналізу пульсового сигналу для підвищення інформативності фотоплетизмографічних систем:

дисертація на здобуття наукового ступеня кандидата технічних наук за спеціальністю 01.05.02 / Лілія Володимирівна Хвостівська. — Тернопіль: ТНТУ, 2021. — 177 с.
15. Talukdar D., Alam M., Rahman M. Evaluation of artificial intelligence methods for atrial fibrillation detection in short-term PPG signals // Computers in Biology and Medicine. – 2023. – Vol. 161. – P. 106987. DOI: 10.1016/j.compbiomed.2023.106987.
16. Aschbacher K., Avery E., Hauser M. et al. Deep learning detection of atrial fibrillation using raw photoplethysmography signals // Heart Rhythm O2. – 2020. – Vol. 1(3). – P. 187–196. DOI: 10.1016/j.hroo.2020.05.005.
17. Yousefi R., Hamilton A., Nault I. Artificial neural network approach for PPG-based AF detection // Proceedings of the Computing in Cardiology Conference. – 2019. – P. 1–4.

DESIGN AND OPERATING PRINCIPLE OF HYDROMECHANICAL WATER LEVEL SENSORS FOR THE APU-200C WATER REGULATOR

Bohush Oleksandr
PhD Candidate
Khlapuk Mykola
DSc (Tech), Professor
Department of Hydraulic Engineering and Hydraulics
National University of Water and Environmental Engineering
Rivne, Ukraine

Currently, the drainage and irrigation systems of Polissia demonstrate a growing demand for reliable, energy-independent, and cost-effective automation of water level regulation. This need is further reinforced by the considerable length of canal networks, seasonal fluctuations in inflow, and the limited financial resources available for system operation.

At the same time, the automation of processes in drainage and irrigation systems requires the application of precise and technologically advanced water level sensors that are integrated into the functionality of hydro-regulators. Consequently, there is a necessity to implement such devices in existing facilities as part of the modernization and reconstruction of outdated infrastructure.

At present, electric water level sensors remain in high demand on the market. However, alongside the progress of science and engineering, hydromechanical sensors have undergone significant improvement, offering an energy-efficient alternative to electrical devices.

Hydro-automatic regulators (such as the ARU-200C type) have proven their effectiveness due to their structural simplicity and energy independence. Nevertheless,