Вісник Тернопільського національного технічного університету
https://doi.org/10.33108/visnyk_tntu
Scientific Journal of the Ternopil National Technical University
2025, № 3 (119) https://doi.org/10.33108/visnyk_tntu2025.03
ISSN 2522-4433. Web: ***visnyk.tntu.edu.ua***

UDC 004.93:612.172:615.825:004.021

COMBINED USE OF WAVELETS AND SLIDING WINDOW FOR PULSE SIGNAL PROCESSING UNDER PHYSICAL LOAD

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Abstract. *The article presents a modern approach to pulse signal processing under conditions of physical exertion and in the recovery phase, which is based on the combined use of wavelet processing and the sliding window method. This approach allows overcoming the limitations of traditional time and frequency methods, providing a multi-scale time-frequency distribution of the signal and its precise temporal localization.*

Particular attention is paid to the use of the 4th-order Daubech wavelet (db4), which provides an optimal balance between sensitivity to sharp changes in the signal during exertion and smoothness in the recovery phase. Wavelet-energy analysis of the signal in the sliding window made it possible to track the dynamics of changes in the cardiovascular system, in particular: an increase in energy during exertion, reaching a peak value and a gradual return of the indicator to the baseline level in the recovery phase.

The key indicator is the recovery time, which is defined as the interval between the moment of reaching peak activation and the return of the signal energy level to the resting state. To automate this process, an algorithm using a threshold device is proposed. At the first stage, a reference interval is selected before the start of the load, which characterizes the baseline wavelet energy at rest. Then, the threshold value is calculated according to the formula: Epor = 1.2 × Ebas, i.e. baseline energy plus 20% tolerance. This value allows you to take into account the variability of the signal and at the same time avoid false positives caused by noise or random fluctuations.

The algorithm defines the recovery moment as the first time interval after physical exertion, in which the wavelet energy value steadily decreases and remains below the calculated threshold. This approach combines objectivity and accuracy, eliminating subjective errors in visual signal analysis.

The practical significance of the developed method lies in the possibility of its application for assessing the fitness of athletes, controlling recovery processes in cardiology, monitoring the condition of patients in rehabilitation medicine, as well as in its implementation in portable fitness devices and telemetry systems. Thus, the combination of wavelet processing, window processing and the threshold recovery time algorithm creates a reliable tool for quantitatively assessing the adaptive capabilities of the cardiovascular system.

Key words: *pulse signal, human vessels, physical activity, wavelet processing, sliding window, algorithm, recovery time, MATLAB.*

https://doi.org/10.33108/visnyk_tntu2025.03.063 *Received 20.07.2025*

1. INTRODUCTION

The study of the processes of recovery of the cardiovascular system (CVS) after dosed physical exertion is a key task of modern physiology, sports and clinical medicine. One of the most informative indicators of the state of the CVS is the structure of the pulse signal, which carries data on vascular elasticity, regulation of peripheral resistance and the rate of hemodynamic changes. In this regard, the analysis of the time points of recovery based on the pulse wave is considered a promising tool for assessing the functional reserves of the body.

Effective methods of processing the pulse signal during physical exertion are a key condition for obtaining reliable information about the functional state of the body and assessing the adaptive capabilities of the CVS.

Existing methods of pulse signal processing can be conditionally divided into time, frequency and time-frequency. Classical time methods allow to estimate amplitude, wavelength and local morphological parameters, however, they do not take into account the spectral component of the signal, which limits them in the study of recovery processes [1]. Frequency methods, in particular Fourier transform, are widely used for processing rhythmic components of pulse signals [2], however, their disadvantage is the loss of temporal information, which reduces the efficiency in the analysis of non-stationary biomedical signals. The use of short-time Fourier transform (STFT) has partially overcome these limitations, however, the fixed processing window creates a compromise between time and frequency resolution [3]. A more flexible approach to the analysis of pulse signals under conditions of physical exertion has become wavelet processing. It provides a multi-level time-frequency decomposition, which allows to simultaneously evaluate both local time features and the spectral composition of the signal. Due to this, wavelet methods are widely used for the study of cardiovascular system, in particular for the isolation of diagnostically significant phases of the pulse wave and the detection of the dynamics of recovery after loads [4, 5]. In [6] it was shown that the wavelet energy and entropy parameters are sensitive to physiological changes during loading and recovery, which makes them effective markers of adaptation processes.

However, even the most effective wavelet processing methods do not always allow to accurately determine the time points of transition between the load and recovery phases. In this context, a promising combination of wavelet transform with the sliding window method is considered, which provides localized processing in time and allows to record transient signal changes with high accuracy [7]. Such a combined approach combines the multi-level time-frequency sensitivity of wavelet processing and the flexibility of the sliding window, which creates new opportunities for more reliable detection of the moments of CVS recovery after dosed physical exertion.

2. PULSE SIGNAL, PHYSICAL ACTIVITY AND RECOVERY TIME

Analysis of changes in the structure of the pulse signal during dosed physical exertion is a universal means of controlling and regulating their intensity, and also allows you to detect hidden pathologies of the cardiovascular system that can lead to sudden death.

The Ruffier test allows you to quickly assess the functional state of the cardiovascular system. It allows you to identify the adequacy of the heart's response to stress and the speed of its recovery in the resting phase. Due to its simplicity and informativeness, the test is widely used in physiology, medicine and sports practice. The methodology and principle of the Ruffier test consist in performing 30 sit-ups in 30 seconds with subsequent registration of the PS at rest, after stress and during the recovery period to assess the state of the cardiovascular system.

Fig. 1 shows the change in the PS of human vessels during the Ruffier test: from the resting state through the stress phase to the gradual recovery of the cardiovascular system.

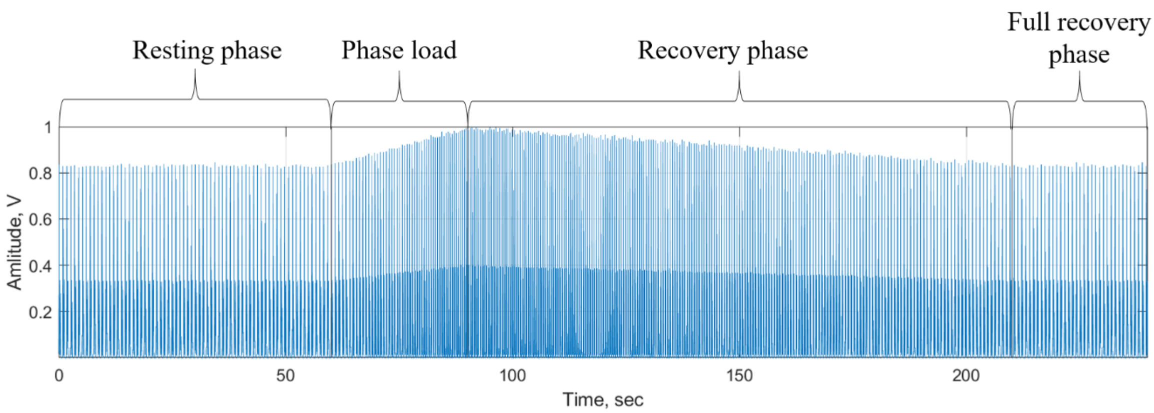

Figure 1. Structure of the pulse signal during physical exertion

According to Fig. 1, in the resting state (0–60 sec) the amplitude of the PS is stable (≈0.7–0.8 V), the pulse rate is moderate, uniform. This phase acts as a baseline for further comparison with the recovery phase.

In the load phase (30 squats, 60–90 sec) there is an increase in heart rate (the heart beats faster to deliver more oxygen), the signal amplitude increases (≈0.9–1.0 V) due to an increase in the stroke volume of the heart.

In the recovery phase (≈90–210 sec) the pulse rate remains elevated, but gradually decreases, the signal amplitude begins to decrease. Some signal unevenness is possible due to active compensatory processes (oxygen deficiency).

In the phase of complete recovery (210–240 sec) the heart rate returns to the initial state of the resting phase, in particular, the amplitude of oscillations decreases to the initial values (~0.7–0.8 V), the heart rate decreases, the peaks are located less frequently.

So, during physical exertion, the heart rate, amplitude and shape of the pulse wave change. After physical exertion, the heart rate and pulse wave change dynamically, in particular, the heart rate decreases, the morphology of the pulse wave stabilizes and the pulse variability gradually returns to normal.

Therefore, processing/analysis of the entire signal «in general» does not reflect the real time when the body has fully recovered. Local processing in time is needed – that is, window processing to determine the recovery time after physical exertion.

Therefore, recovery time is one of the key indicators for assessing cardiovascular health, athlete fitness, and the risk of cardiovascular complications. After exercise, a normal person quickly restores stable pulse parameters (1-3 min). A delay in this time is an indicator of overfatigue, overtraining, or pathology.

3. WINDOW PROCESSING OF PULSE SIGNAL

Sliding window is a method that allows you to limit the processing to only a part of the PS around time $t=b$. This is implemented using a window function $D(t-b)$, which has a non-zero value only within the interval $[b-L/2,\ b+L/2]$, where L is the window width (number of points).

The sliding window allows:

– to monitor the dynamics of changes in the structure of the PS;
– to detect the time point when the parameters return to the baseline (resting state);
– to determine the time of achieving stability of the CVS.

This is important for determining the individual level of fitness or cardiac reserve.

Algorithmic advantages of window processing of the PS:

– window processing allows for real monitoring, including on portable devices (fitness bracelets, heart rate monitors),
– allows for adaptive processing: for example, changing the width of the window according to the rate of signal changes,
– suitable for online processing, for example, in sports medicine or telemetry.

The reasons for using PS window treatments are given in Table 1.

Table 1

Advantages of using windowed pulse signal processing

Reason	The role of windowing
PS non-stationarity	Detecting local changes
Restoration dynamics	Determining the time to return to the resting state
PS frequency variability	Assessing adaptation of the autonomic nervous system
Individual approach	Adapting window width to the rate of recovery
Implementation in real-time devices	Optimal processing speed and energy efficiency

3. COMBINED USE OF WAVELET AND SLIDING WINDOW FOR PULSE SIGNAL PROCESSING

The combined use of wavelet and sliding window for processing the pulse signal $x(t)$ in time space is a modern, effective and justified approach, especially when studying the response of the cardiovascular system to physical exertion.

Wavelet transformation allows you to process and analyze simultaneously the temporal and frequency structure of the signal, identify local features, vascular response to exertion and the appearance of pathological components.

During exertion, wavelet processing allows you to track systolic activity and frequency peaks, and during recovery – to assess the moment of stabilization of parameters.

Practical value:

– in sports: assessment of fitness, training effectiveness.
– in cardiology: detection of arrhythmias, hypertension, ischemia.
– in rehabilitation: monitoring of the condition after stress.
– in fitness devices: real-time integration for health monitoring.

Wavelet processing of PS using the sliding window method is a highly effective tool for analyzing the body's physiological responses to physical exertion, allowing for accurate assessment of both the loading and recovery phases.

Suppose we have a digital (discrete) PS:

$$x(t),\quad t = 0, \Delta t, 2\Delta t, \ldots, T\,, \tag{1}$$

where Δt – discretization step, T – total flight duration.

Continuous wavelet transform allows to decompose the PS into time-scale components:

$$W(a,b) = \int_{-\infty}^{\infty} x(t)\psi^{*}_{a,b}(t)dt\,, \tag{2}$$

where $\psi^{*}_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)^{*}$ – scaled and shifted wavelet function;
a – scale (inversely proportional to frequency);
b – time shift (window centering);
$\psi(t)$ – mother (base) wavelet.

Therefore, to localize the processing of the PS in time, the window function $w(t)$ was used, which limits the calculations within the interval of N points.:

$$x_w(t;b) = x(t)w(t-b)\,, \tag{3}$$

where $w(t-b)$ – window function shifted to time b.

Thus, the processing is performed only for the PS fragment around time point b by combining a sliding window and a wavelet transform:

$$W(a,b) = \int_{-\infty}^{\infty} x(t)w(t-b)\psi^{*}_{a,b}(t)dt\,. \tag{4}$$

This allows performing localized PS analysis in each window centered at b.

Discrete view in computer processing:

$$W[a,b]=\sum_{n=0}^{N-1} x(n\Delta t+b)w(n)\psi^{*}_{a,b}(n\Delta t), \tag{5}$$

where a – scale: large a corresponds to low frequencies (slow changes), small a – high-frequency oscillations (fast changes).
b – time offset: the position of the center of the window where processing is performed.
$w(t)$ – window function: Gaussian, rectangular, Hamming, etc., which defines the processing boundaries.

The result is a matrix of coefficients $W(a,b)$, which reflects how the signal energy changes over time and scale.

This allows you to detect changes in pulse wave morphology, arrhythmias, or vascular pathology.

If necessary, it is possible to restore the PS from wavelet coefficients:

$$x(t)=\frac{1}{C_{\psi}}\int_{0}^{\infty}\int_{-\infty}^{\infty} W(a,b)\psi_{a,b}(t)\frac{dbda}{a^2}, \tag{6}$$

where C_{ψ} – normalization constant, depending on the choice $\psi(t)$.

The final formula of the combined PS processing model:

$$W[a,b]=\sum_{n=0}^{N-1}\left[x(n\Delta t+b)w(n)\right]\psi^{*}\left(\frac{n\Delta t}{a}\right), \tag{7}$$

where $w(n)$ – window function (e.g. rectangular, Gaussian, Henning, etc.);
Δt – time discretization step;
b - time shift (window position on PS);
a – wavelet scale (analog of frequency: small a = high frequencies);
$\psi*(\cdot)$ – complex conjugate wavelet function;
N – number of points in the window.

This model takes into account both locality in time and multiscale processing, which is especially important for physiological signals and allows you to accurately track the body's response to physical exertion, determine the moment of recovery, detect artifacts or pressure changes.

Choosing the optimal window width for wavelet processing of PS is a compromise between time and frequency resolution [8, 9]. Too narrow a window gives good time localization, but poor frequency. Too wide – the opposite. That is why in wavelet processing the scale a also controls the window width: the larger the scale, the wider the window in time.

Recommended window settings:

– width: 25 seconds (optimal value for time accuracy and frequency stability) [8, 10];
– range: 20-30 sec [11];
– maximum: 60 sec (for stationary HRV analysis) [9];
– shift step: 0.1–0.2 seconds for graphic detail [10].

Adopting these parameters ensures accurate detection of the moment of system recovery after physical exertion with an accuracy of up to tens of seconds [8, 12].

4. SELECTING A WAVELET BASIS FOR WINDOWED PULSE SIGNAL PROCESSING

The 4th-order Daubechie wavelet (db4) is one of the most common orthonormal wavelets, especially when processing pulse, cardiac (ECG, PPG), tremor, or respiratory signals. It is justified both theoretically and practically.

db4 provides a balance between localization in time and frequency and has a short support (filter length), which allows you to well detect sharp changes in the signal (for example, the phase after physical exertion).

At the same time, it has sufficient smoothness to capture longer wave structures of PS.

Since PS has a non-stationary nature (its shape and frequency change over time (due to breathing, exercise, stress)), db4 allows you to adaptively decompose the signal into scales (frequencies) and detect local changes.

db1 (i.e. Haar) is too coarse – it will cut off important details, db6, db8, etc. – have higher smoothing ability, but lose accuracy in temporal detection of events.

Therefore, db4 is an optimal compromise between smoothing and accuracy.

Table 2 shows the advantages of using the 'db4' wavelet.

Table 2

Advantages of using the 'db4' wavelet

Phase	Important properties of wavelets	Advantage of 'db4'
During load	Detection of abrupt changes	Sensitive to impulses, acceleration
Recovery	Smoothing/dynamics	Detects slowing of the pulse
Transitional areas	Frequency/time tradeoff	Remains accurate

The formula for the 4th order Daubech wavelet (db4) describes the wavelet function and the scaled mother function in terms of convolution coefficients (filters). The db4 wavelet has four smoothing filter coefficients *h*.

Wavelet function:

$$\psi(t) = \sum_{0}^{7} q_k \phi(2t - k), \tag{8}$$

where q_k – scaling filter coefficients;

$q_k = (-1)^k h_{7-k}$ – wavelet filter coefficients (derived from h_k);

$\phi(t)$ — zoom function;

(t) — wavelet function.

Filter coefficients for db4:

h_0=−0.0105974017850021,

h_1=0.0328830116668852,

h_2=0.0308413818355607,

h_3=−0.1870348117188811,

h_4=−0.0279837694168599,

h_5=0.6308807679295904,

h_6=0.7148465705525415,

h_7=0.2303778133088964.

The scale filter h_k extracts low-frequency information, and the wavelet filter q_k extracts high-frequency components of the PS.

In the context of a PS: db4 allows you to delicately process and analyze transients and localize changes during physical exertion.

5. WAVELET ENERGY AS AN INDICATOR OF PULSE SIGNAL RECOVERY AFTER PHYSICAL EXERTION

Wavelet energy is a quantitative assessment of the energy of local frequency components of a wave, which allows:
- analyze the frequency content of the PS over time;
- detect dynamic changes in pulse structure;
- study nonlinear and non-stationary systems.

Wavelet energy shows the «strength» of a physiological state, in particular:
- during physical activity, wavelet energy increases;
- after – decreases as recovery occurs;
- return to initial energy level = body recovered.

This allows you to objectively measure the state of the cardiovascular system.

Without energy calculation, only a «raw» signal is obtained (visual viewing, manual interpretation).

Wavelet energy = an objective, numerical characteristic that:
- easily processed and analyzed;
- used in threshold algorithms;
- allows you to automate the determination of recovery time.

Wavelet energy is a numerical measure of the total energy of a signal in a certain frequency range in a limited time window. It is determined by the square of the amplitudes of the wavelet coefficients in the time window D:

$$E_j = \sum_{a \in D} \left| W(a,b) \right|^2 . \tag{9}$$

Therefore, calculating wavelet energy is a necessary step in the processing of PS, especially during physical exertion. It is the only method that gives:
- detailed, localized assessment of PS activity;
- numerical basis for identifying the recovery moment;
- flexibility and accuracy for use in automatic diagnostic, monitoring and training systems.

6. RESULT OF WINDOWED WAVELET PROCESSING OF A PULSE SIGNAL

Fig. 2 shows the result of window wavelet processing (Daubech basis) of the PS during physical exertion in the Matlab environment with subsequent calculation of the wavelet energy.

In the time interval up to ~40 sec, a stable low-amplitude level of the indicator (E≈0.15 V^2) is observed, which reflects the basic state of regulatory mechanisms during the rest phase. During the load phase, starting from 40-45 sec, an intensive increase in energy is noted, which reaches a maximum value (E≈0.40 V^2) in the range of ~80-90 sec. This stage corresponds to the phase of peak activation of autonomous regulation and strengthening of the oscillatory structure of the PS under the influence of post-load adaptation.

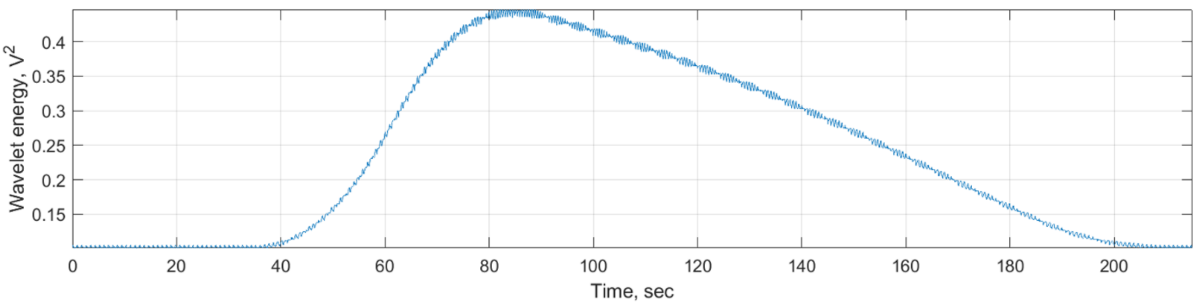

Figure 2. Dependence of wavelet energy of PS on time

The subsequent time interval (~90–200 sec) is characterized by a monotonic decrease in wavelet energy with preservation of oscillatory dynamics, which indicates a gradual restoration of functional activity and return of cardiovascular system parameters to the initial level (recovery phase). This signal behavior is consistent with the phase structure of the post-load response: the transition from the activation peak to the recovery stage, which can be used as an objective marker of the body's adaptive reserves.

To automatically determine the moment of recovery after physical exertion, visual analysis of the graph alone is not enough (Fig. 2), because:

– energy fluctuates due to natural biological dispersion and signal noise.

– visual assessment is subjective and depends on the operator's experience.

In real-time conditions, automatic decision-making is required without human intervention.

The threshold device allows:

– determine the baseline energy level at the initial (pre-load) interval.

– set a threshold (e.g. baseline + some tolerance) below which energy is considered recovered.

– control the moment when the wavelet energy after the peak steadily drops and stays below the threshold for a given time (to avoid false positives due to random fluctuations).

Thus, the threshold device provides an objective, fast and stable determination of the recovery time, which is important in medical monitoring systems and sports diagnostics.

The recovery threshold is set to detect the moment when the vascular pulse signal returns to the «normal» state after physical exertion. This is done through the analysis of the energy of the wavelet components in the time space using the sliding window method.

The algorithm for finding the recovery time is shown in Fig. 3.

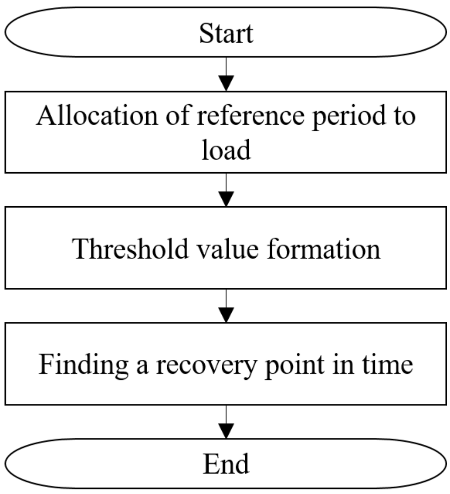

Figure 3. Algorithm for finding recovery time after physical exertion

At the stage of allocating a reference period to the load:

– The time interval before the start of physical activity (rest phase period) is selected.

– Wavelet energy during this period is considered reference or background activity.

– The average energy value in this rest state is calculated.

At the threshold value formation stage, the threshold level for making a decision on restoration is selected/selected.

In works on biosignal analysis (e.g., [1], [4]) it is shown that:

– too low threshold (<115%) → high sensitivity, but many false positives;

– too high threshold (>130%) → misses real changes (low sensitivity);

– the value of 120% corresponds to the ROC optimum in similar decision-making tasks (Receiver Operating Characteristic): maximizing the area under the AUC curve in rhythm restoration tasks [4].

The threshold value is set as 120% of the baseline energy level (i.e. baseline energy + 20% reserve).

Setting the threshold at +20% allows:

– ignore small fluctuations (i.e. do not react to noise);
– detect true recovery when energy has returned to background.

In wavelet processing, the energy of the frequency coefficients indicates the dynamic activity of the signal:

– during load → energy increases significantly (sometimes 2-3 times).
– after recovery → returns to baseline.

The 120% threshold provides a safe cutoff below which the signal is considered inactive or restored. This allows you to take into account small fluctuations not related to the load (pulsation, noise).

The method corresponds to the concept of threshold decision making, when:

– if the energy is below the threshold → the signal is considered to have stabilized;
– if higher → signal still unstable (load effect continues).

The value of 120% is a compromise between sensitivity and specificity:

– lower threshold → risk of false positive;
– higher threshold → recovery signal may be missed (false negative).

At the stage of searching for the moment of recovery:

– the search begins after the loading phase ends.
– is checked: when the energy first falls below the threshold, this moment is considered the point of recovery of vascular activity.

Table 3 summarizes the rationale for the methodology and the corresponding justifications.

Table 3

Justification of the methodology for finding recovery time after physical exertion

Algorithm steps	Justification
Select base energy before loading	This is a «standard» of the body's resting state
Threshold = 1.2 × base energy (pre-load state)	Takes into account natural variability + margin for reliability
Search after loading	Determines the real time when the body has returned to normal

Fig. 4 shows the results of calculating the time point of CVS recovery after physical exertion based on wavelet energy data and threshold level data.

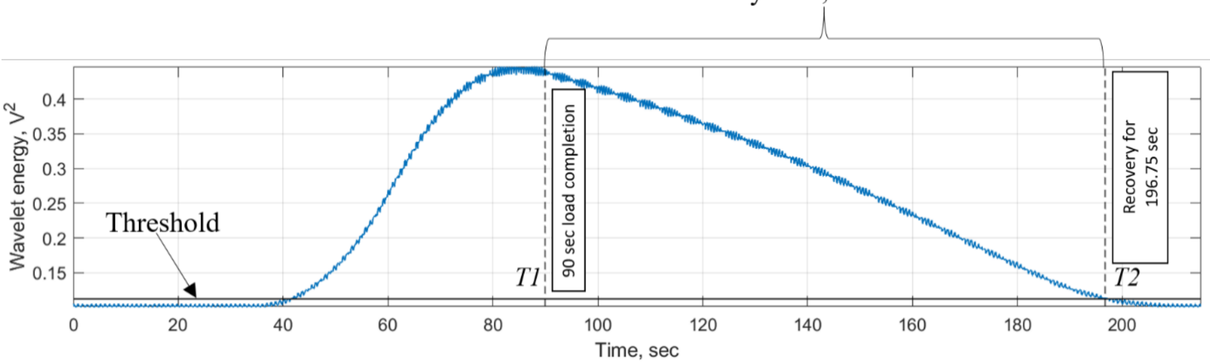

Figure 4. Dependence of wavelet energy of PS on time with marked time moments and threshold

According to Fig. 4. in the initial section of the curve (0-40 s) the energy value is at the base level (E≈0.15 V^2) below the threshold value. After exceeding the threshold value, a rapid increase in the energy indicator is observed, reaching a maximum in the range of 90 s. The time of reaching the peak value is designated as T1. Further dynamics is characterized by a gradual decrease in energy, which reflects the CCS recovery phase. The moment when the wavelet energy value decreases to the threshold value from the peak level in the descending section is designated as T2.

The recovery time (Trec) is calculated as the difference between these timestamps:

$$T\text{rec}=T2\text{-}T1=196{,}75\text{sec - 90 sec}= 106{,}75 \text{ sec.} \tag{10}$$

Thus, the proposed approach allows us to quantitatively assess the rate of return of the cardiovascular regulatory mechanisms to the initial level after physical exertion using the recovery time indicator Trel.

7. CONCLUSIONS

The combined use of wavelet processing and the sliding window method provides multi-scale and time-localized processing of the pulse signal, which allows you to accurately track both the phase of physical exertion and the process of recovery of the cardiovascular system.

The use of wavelet energy as a numerical indicator allows you to quantitatively determine the recovery time after exertion, when the physiological parameters of the cardiovascular system return to baseline values.

The use of a threshold device with a level of 120% of the baseline energy eliminates the subjectivity of the assessment, allows you to automate the determination of the moment of recovery and increases the reliability of the method for practical use in sports medicine, cardiology and real-time monitoring systems.

Prospects for further research include the development of adaptive threshold algorithms with dynamically formed decision levels, the expansion of wavelet bases and multiresolution approaches, the integration of machine-learning methods for automatic functional-state classification, the creation of real-time embedded monitoring systems, the clinical validation of the proposed methodology on diverse population groups, and the investigation of multi-parameter monitoring through the combination of wavelet pulse characteristics with respiratory, HRV and impedance-cardiography signals.

Thus, the proposed approach forms a reliable methodological basis for quantitative assessment of the recovery processes of the cardiovascular system, and its further development will contribute to the creation of intelligent diagnostic and monitoring systems in sports, cardiology and personalized medicine.

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УДК 004.93:612.172:615.825:004.021

КОМБІНОВАНЕ ВИКОРИСТАННЯ ВЕЙВЛЕТ І КОВЗНОГО ВІКНА ДЛЯ ОПРАЦЮВАННЯ ПУЛЬСОВОГО СИГНАЛУ ПРИ ФІЗИЧНОМУ НАВАНТАЖЕННІ

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Резюме. *Представлено сучасний підхід до опрацювання пульсового сигналу в умовах фізичного навантаження та у фазі відновлення, який базується на комбінованому використанні вейвлет-опрацювання та методу ковзного вікна. Такий підхід дозволяє долати обмеження традиційних часових та частотних методів, забезпечуючи багатомасштабний часо-частотний розклад сигналу та його точну часову локалізацію. Особливу увагу приділено використанню вейвлета Добеші 4-го порядку (db4), який забезпечує оптимальний баланс між чутливістю до різких змін у сигналі під час навантаження та згладженістю у фазі відновлення. Вейвлет-енергетичне опрацювання сигналу в ковзному вікні дозволила відстежити динаміку змін серцево-судинної системи, зокрема: зростання енергії під час навантаження, досягнення пікового значення та поступове повернення показника до базового рівня у фазі відновлення. Ключовим показником виступає час відновлення, який визначається як проміжок між моментом досягнення пікової активації та поверненням енергетичного рівня сигналу до стану спокою. Для автоматизації цього процесу запропоновано алгоритм із використанням порогового пристрою. На першому етапі обирається еталонний інтервал до початку навантаження, що характеризує базову вейвлет-енергію у спокої. Далі обчислюється порогове значення за формулою Епор=1,2×Ебаз, тобто* *базова енергія плюс 20% допуску. Це значення дозволяє врахувати варіабельність сигналу та одночасно уникнути хибних спрацьовувань, зумовлених шумами чи випадковими коливаннями. Алгоритм визначає момент відновлення як перший часовий інтервал після фізичного навантаження, в якому значення вейвлет-енергії стабільно знижується й тримається нижче обчисленого порогу. Такий підхід поєднує об'єктивність та точність, усуваючи суб'єктивні похибки візуального аналізу сигналу. Практична значущість розробленої методики полягає в можливості її застосування для оцінювання тренованості спортсменів, контролю відновних процесів у кардіології, моніторингу стану пацієнтів у реабілітаційній медицині, а також у впровадженні в портативні фітнес-пристрої та системи телеметрії. Таким чином, поєднання вейвлет-опрацювання, віконного опрацювання та алгоритму порогового визначення часу відновлення створює надійний інструмент для кількісного оцінювання адаптаційних можливостей серцево-судинної системи.*

Ключові слова: *пульсовий сигнал, судини людини, фізичне навантаження, вейвлет опрацювання, ковзне вікно, алгоритм, час відновлення, MATLAB.*

https://doi.org/10.33108/visnyk_tntu2025.03.063 *Отримано 20.07.2025*