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DISCRETE WAVELET TRANSFORM DENOISING METHOD EFFICIENCY EVALUATION FOR PROCESSING PULSE SIGNALS WITH HARMONIC COMPONENTS

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Abstract. *This article reviews the problem of parameter selection for denoising methods based on the Discrete Wavelet Transform (DWT) for processing geo-signals with various noise types and external interference, followed by evaluating the effectiveness in detecting recurring signal patterns. The study reviews the theoretical impact of denoising parameters, existing wavelet and decomposition level selection methods, publications on DWT applications in different fields, and the computational challenges of increasing decomposition levels for microcontrollers. Experimental results of DWT denoising application on field-gathered signals recorded in different environments, presented as average SNR changes for specific DWT parameter combinations. Comparison of results by decomposition levels showed gradual improvements in efficiency with certain wavelets and significant drops after specific levels in some cases due to the filtering of typical samples, which emphasizes the need to review DWT parameters only in the scope of specific parameter combinations. Notable anomalies in efficiency due to the non-stationary nature of signals and parameter resonance with noise or patterns were also observed, requiring further research. Based on the findings, the most effective parameter combinations for denoising the studied geo-signal were identified, with a particularly optimal combination of three decomposition levels, hard thresholding, and rbio3.3 wavelet, which preserved and even amplified signal energy while enabling the detection of typical fragments at distances of 120–100 meters.*

Key words: *discrete wavelet transform, DWT, denoising, pulse signal, signal processing, non-stationary signal, pulse signal, geo-signal.*

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1. INTRODUCTION

The Discrete Wavelet Transform (DWT) is a crucial tool in signal processing, particularly for signal analysis and denoising. By decomposing a signal into wavelet coefficients, the DWT allows for multi-resolution analysis, providing both time and frequency localization. This makes it especially effective for handling non-stationary signals in various fields such as geosciences [1], engineering [2], medicine [3], etc.

Signal denoising using DWT has been successfully applied in various fields such as denoising biomedical signals [4, 5], acoustic emission signals [6], rail surface ultrasonic wave signals [7], and more. The DWT is favored for its ability to reduce entropy, offer multiple resolutions, and provide decorrelation, which collectively contributes to its effectiveness in noise reduction [6]. Moreover, the multiresolution property of the DWT is particularly advantageous for signal denoising as it can accurately describe nonstationary signal characteristics [8].

Commonly denoising methods are compared to Fast Fourier Transform based denoising method which have its own drawbacks. Such denoising method usage is problematic due to the appearance possibility of the Gibbs phenomenon and its low effectiveness in obtaining partial characteristics of sensor signal [9]. In some cases, the wavelet transform denoising method may

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lead to worse SNR results than the FFT denoising method. For example, the comparison of denoising methods applied on partial discharge signal demonstrated that the DWT denoising method has lower efficiency than the FFT-based method, and even degraded SNR compared to unprocessed noisy signal [10].

Innovative approaches have also been proposed to enhance denoising effectiveness which are using wavelet transform. For instance, an adaptive noise removal method for EEG signals integrated wavelet denoising with minimum mean square error (MMSE) and an adaptive threshold-based LMS algorithm to enhance denoising accuracy [11]. Additionally, an integrated denoising method based on wavelet packet transform and energy-correlation analysis was developed to address sensor mixed noises in industrial settings [9].

The discrete wavelet transform stands out as a powerful tool for signal denoising across various domains, including geophysics, owing to its multiresolution property, noise reduction capabilities, and adaptability to different signal types. Researchers are continuously exploring novel techniques and combinations to further enhance the denoising efficiency and accuracy of the DWT in practical applications.

2. PROBLEM OVERVIEW

Researched pulse signal with harmonic components stores information captured on a range of distances up to 150m. The signal was captured by sensor GD-10 during field experiments with a developed autonomous device based on an 8-bit microcontroller ATmega328p with embedded 10-bit resolution ADC [12], a sample rate of 100 Hz, which satisfies the conditions of the Nyquist-Shannon theorem based on the geo-signal frequency spectrum range. The captured digital signal was transferred through a UART interface. The main goal of the researched signal processing is the detection of time fragments where repeated typical samples appear (Fig. 1), where *smpl* is the sample ADC value, and *i* is an ordinal number of the sample. Used geo-sensor can capture low amplitude signals with searched typical samples which can be observed visually up to 120m. Automatic detection approaches are limited by the computational capabilities of the microcontroller and are complicated by white noise, external interfering sources, and signal distortion affected by distance to the observed signal source [13].

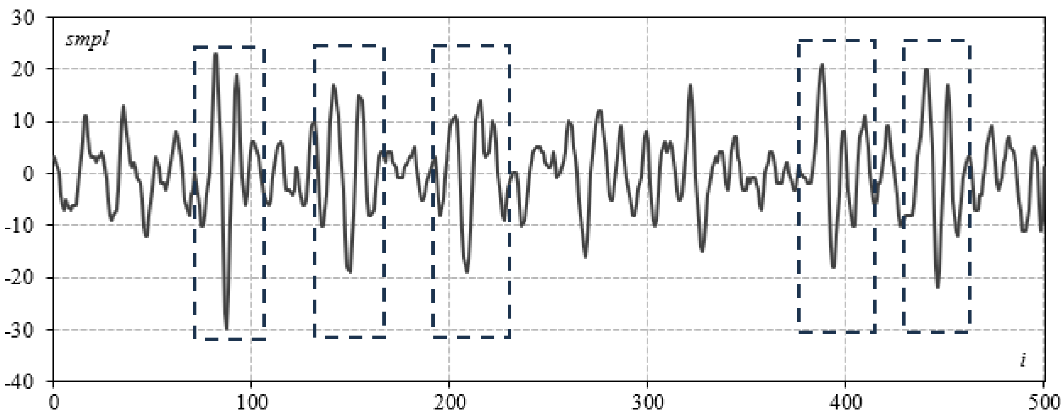

Figure 1. Searched typical samples in geo-signal

The first attempt to recover a typical fragment from a noisy signal was conducted with a list of correlation function applications and their comparison by SNR [14]. The usage of correlation functions was explained by similar characteristic features of searched typical fragments, which may be recovered by correlation of geo-signal to prepared templates formed from a stack of manually recovered typical samples. From the used correlation functions only 3 out of 8 provided better results than the input signal. The best of those functions improved SNR by 44.5% on average and allowed the capture of typical fragments with amplitude threshold up to 80m, which is still less than can be captured by manual search.

Further research showed that the frequency spectrum of noise and recorded signal overlaps [13]. With a distance longer than 60m signal is getting closer to noise in a frequency range, and is in the same frequency ranges, within 2–17 Hz (Fig. 2), which explains why it is problematic to recover typical samples from longer distances. The application of filters based on FFT provided worse results than some correlation functions [15]. Filter application on the same signal used in correlation functions testing, showed SNR results improvement by 14%, which is 6% less effective than the relay correlation function in denoising capabilities. That information gave us an understanding that signal recovery based on methods that rely on frequency spectrum are less effective than those that rely on signal form and characteristic features.

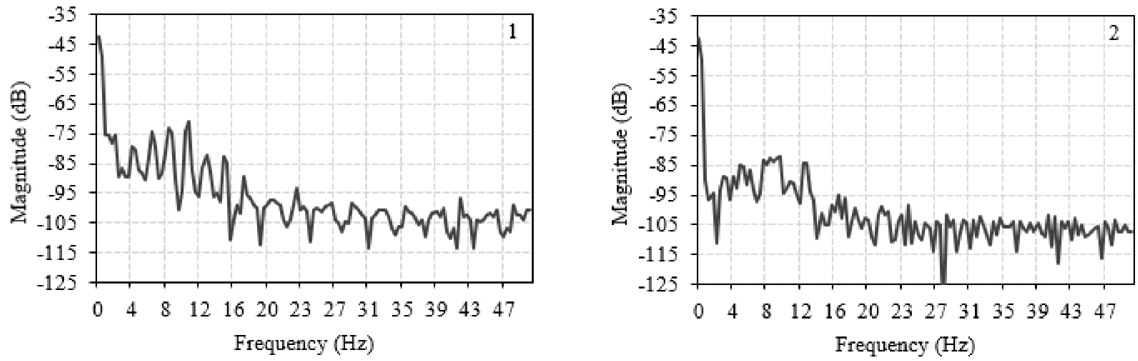

Figure 2. Frequency spectrum of input signal (1) and noise (2)

DWT is similar in some points of view to correlation functions, both involve convolution and time-shifting operations. Although the DWT denoising method uses an ability to isolate and manipulate frequency components to reduce noise, which is already confirmed as a less effective way of researched signal processing targeted at the detection of repeated typical samples, it can't be ignored how commonly and widely that tool is used for signal denoising, including geo-signals denoising, which is the type of signal what is being processed and researched, and that assumption of method efficiency requires experimental confirmation. Unlike FFT, which provides only frequency information, DWT offers both time and frequency localization. This helps in the identification and denoising of transient noise, such as spikes or bursts, which can be found in the researched geo-signal.

3. DWT DENOISING PROCESS AND RESULT EVALUATION

The denoising process based on DWT can be divided into three steps (Fig. 3) – analysis, thresholding, and synthesis. The analysis step uses forward wavelet transform to decompose signal into high-frequency and low-frequency components using scaling and wavelet functions. The threshold step applies a thresholding function on received components to remove noise. The synthesis step reconstructs the signal from thresholded coefficients by using inverse DWT.

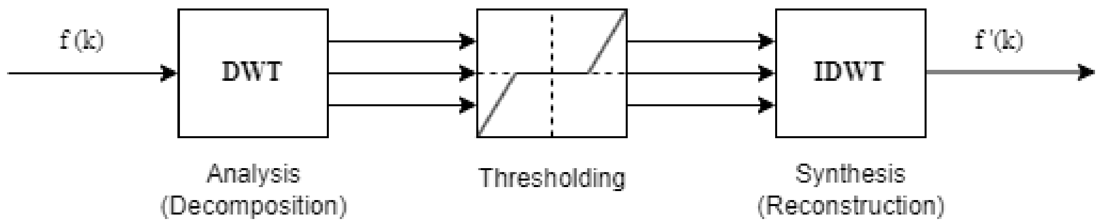

Figure 3. Schematic representation of DWT denoising process

The choice of wavelet in DWT can significantly impact the results of denoising. The wavelet function affects how the signal is decomposed into approximation and detail coefficients, which in turn influences how effectively noise is reduced and how well the signal is preserved. There are existing automated methods for wavelet selection based on correlation, signal energy, and SNR, but in this article, it was decided to use a list of widely used discrete wavelets and score their efficiency through the conduction of the experiment and SNR comparison [16]. In the scope of this research, the following wavelet families were used: Haar, Daubechies, symlets, coiflets, biorthogonal, reverse biorthogonal, and discrete Meyer. Also included into consideration wavelet order, because it can affect computational complexity and noise filtering efficiency.

A threshold is another component of the denoising process that may have a high impact on the result of the denoising process since that step filters noise components out of the researched signal by removing the coefficients relevant to specific threshold value [17]. During experiments, the two most popular thresholding methods were compared – hard and soft.

Hard thresholding (1) removes coefficients with magnitudes below the threshold, which effectively eliminates noise components associated with small coefficients. [18] However, this can also remove important signal details if those details are represented by small coefficients. This method can introduce discontinuities and artifacts at the boundaries where coefficients are set to zero. The abrupt removal of coefficients can result in a signal that has noticeable jumps or irregularities. Large coefficients are preserved, which can maintain prominent features of the signal. However, fine details may be lost if they are associated with smaller coefficients. Hard thresholding may also give rise to ringing and pseudo-Gibbs phenomenon in reconstructed signals [19]

$$\overline{W_{j,k}^{h}} = \begin{cases} W_{j,k} & \left|W_{j,k}\right| \geq \lambda \\ 0 & \left|W_{j,k}\right| < \lambda \end{cases} \tag{1}$$

Soft thresholding (2) shrinks coefficients towards zero, which helps in reducing noise while preserving more of the signal structure [18]. The gradual reduction of coefficient magnitudes tends to smooth out the signal, reducing the effect of noise. This method generally produces a smoother denoised signal compared to hard thresholding. By shrinking coefficients, it avoids abrupt changes and discontinuities, leading to a more natural-looking reconstruction. Soft thresholding tends to preserve more of the signal's smooth features. However, it may still over-smooth the signal if the threshold is not chosen carefully, leading to a loss of fine details.

$$\overline{W_{j,k}^{s}} = \begin{cases} Sign\left(W_{j,k}\right) \cdot \left(W_{j,k} - \lambda\right) & W_{j,k} \geq \lambda \\ 0 & W_{j,k} < \lambda \end{cases} \tag{2}$$

Another considerable parameter in DWT denoising is the decomposition level (Fig 4) [20]. Each level has own pair of low-pass filter *h* for approximation and high-pass filter (g) for detail, followed by dyadic decimation. By convolving the input signal with the following filters on the first level we receive sets of approximation coefficients cA_1 and detail coefficients cD_1. Then on the next level, the same process applies to approximation coefficients from the previous level.

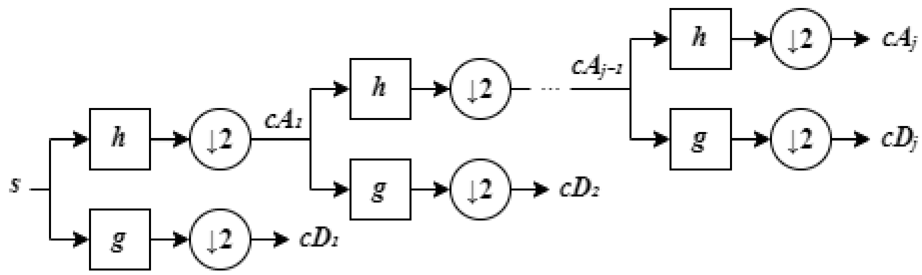

Figure 4. Decomposition with j-level DWT.

By increasing the decomposition level, we increase the number of decomposition steps, and, as a result, increase calculation complexity, which can be especially problematic for microcontrollers. Too small decomposition level may not provide enough denoising results and too high level may not provide a significant efficiency increase related to calculation complexity increase. Traditional methods determine the optimal decomposition level through trial and error or according to the frequency spectrum distribution before a noisy signal is processed by wavelet transform, however, it is expert-dependent and subjective [20]. Publication [21] introduced an automatic method, where the maximum decomposition level can be estimated based on the energy spectral density of the signal. Also, publications [22] and [23] introduced a method to estimate minimal decomposition level based on the energy-ratio threshold, which can help retain signal energy and keep the computational task at a minimum. The simplest method to calculate the maximum denoising level (3) is based on signal length N, but it may be unreliable in cases of noisy signals or long signals [18].

$$L_{max} = \log_2(N) \tag{3}$$

In this article, we relied on the limitations of the microcontroller, and the range of typical samples length to estimate the maximum decomposition level. According to previously conducted research [13] the majority of searched signal fragments have lengths up to 20 samples, but on longer distances in rare cases, we can observe fragments with lengths up to 30 samples, which we will consider as our signal window width. We can use the method based on signal length, due to the small length of signal window that we process, and microcontroller limitations, which don't allow us to set a high level of decomposition. By calculating the maximum decomposition level based on the window length of 30 samples (3), we receive a level equal to 5, which gives us a decomposition bandwidth of 3.13 Hz. That maximum level is sufficient for the research, because higher levels of decomposition would be practically too high for the used microcontroller, and we would be able to see dynamics of SNR change with level increase, so a larger range of decomposition level would be unnecessary.

To evaluate the efficiency of denoise results with specific wavelets application, thresholding methods, and decomposition level, we calculated the SNR of input and output signal according to the used formula in previous research [14] as a relation of signal and noise energies (4)

$$SNR = \frac{E_s}{E_n} \tag{4}$$

For the evaluation of DWT denoising efficiency on researched geo-signal, we compared denoised signal SNR with input signal SNR from the set of recorded signals during field studies in different environments. All fragments taken have equal lengths of 500 samples. Denoise results were formed with varying parameters of input, such as the used wavelet, thresholding method, and decomposition level, which will provide information on how those parameter combinations affect the denoising process result of the researched signal.

4. EXPERIMENT RESULTS

Gathered SNR results of DWT denoising with different parameters applied on the set of signals gathered in field experiments, showed that highlighting the effect of parameter change is complicated because of the instability of results in the set of signals and parameter changes. Moreover, there were captured anomaly results when wavelets were providing worse SNR than the input signal but at some parameters, SNR improved multiple times. The same applies to other named parameters, which complicates the evaluation of preferred parameters for the researched geo-signal. Those anomalies may appear due to the non-stationary nature of the geo-signal and resonance of picked denoising parameters with processed signal segment characteristics and require separate research. More important is the stability of SNR improvement with specific parameters through all the sets of signals after the DWT denoising application, which will tell that the chosen parameters have stable results of denoising for all captured noise, and not only for specific noise characteristics that may appear.

To reduce the effect of results instability and anomaly appearance, according to the results, we excluded parameters that gave us negative results for some signals and gathered average SNR change with specific parameters through the set of signals. Wavelets that provided the best results of hard threshold (Fig. 5) and soft threshold (Fig 6) were provided in the form of a 3D chart to visualize the dynamics of decomposition level (L) change for each wavelet by the value of SNR increase after denoising process in percents (*SNR incr.*).

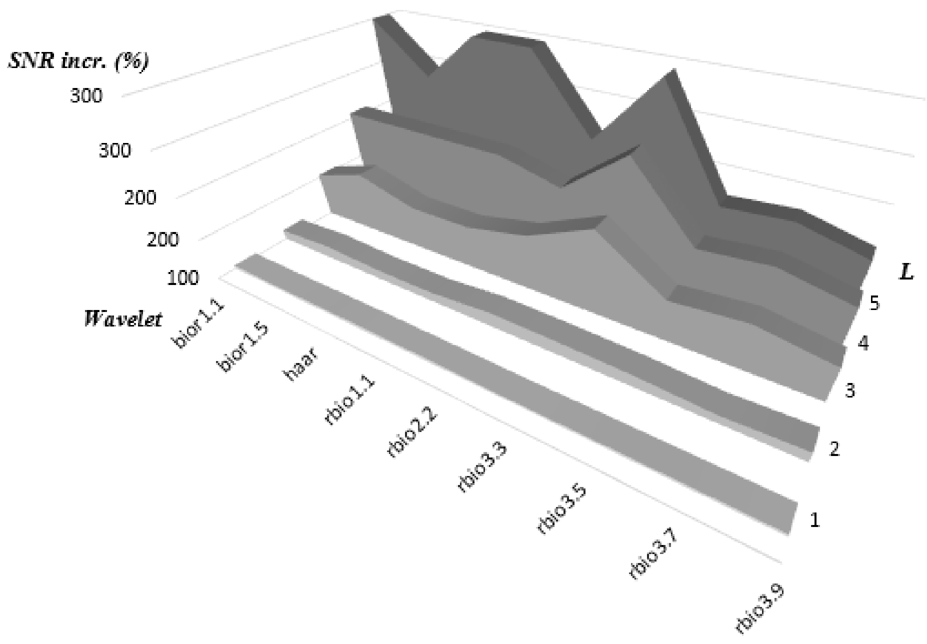

Figure 5. The best results of SNR improvement for the hard thresholding

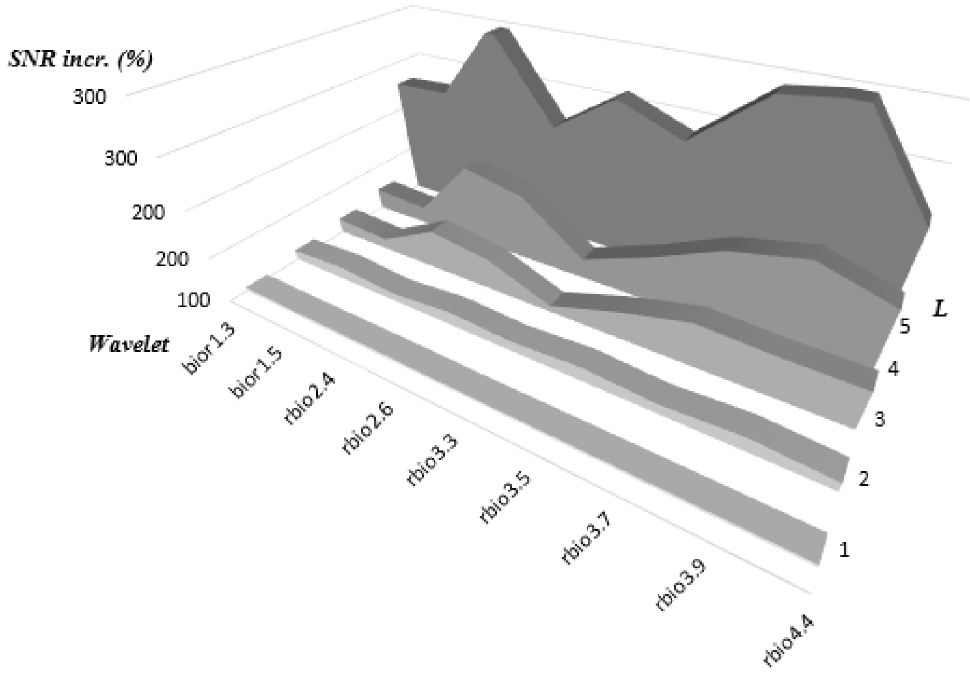

Figure 6. The best results of SNR improvement for the soft thresholding

Change of the threshold method showed that with 5 levels of decomposition, we achieved better results with most of the wavelets, although the results differences were close. As we can see soft threshold for highlighted wavelets has visible efficiency growth on 4 levels and with some wavelets on 5 levels of decomposition. With a hard threshold, we get more gradual SNR growth, which allows us to use fewer decomposition levels to optimize computational tasks for the microcontroller. As we can see in the Table 1, the average SNR on 3 and 4 levels of decomposition *L* is around 50% larger with the hard threshold.

Table 1. The most effective parameters per decomposition level

L	Hard threshold		Soft threshold	
	Avg. SNR improvement	Wavelet	Avg. SNR improvement	Wavelet
1	104%	sym2	104%	sym2
2	119%	rbio3.1	119%	rbio3.1
3	201%	rbio3.3	148%	rbio3.7
4	244%	rbio3.3	197%	rbio3.9
5	301%	bior1.1	306%	rbio2.4

As already mentioned, the majority of wavelets showed the best result with 5 levels of decomposition, although some cases showed a fall in efficiency after some level or just for a specific level. Those cases may be caused by filtering out of some searched fragments. From the selected list of wavelets, the best results were found mostly for the reverse biorthogonal wavelets family. Also worth mentioning are haar and db1 wavelets which provided rapid growth on 4 and 5 levels of decomposition with around 200% and 300% average SNR respectively with the hard threshold method.

Through many parameter combinations, the best results showed average SNR improvement by three times compared to an input signal with 5 levels of decomposition, soft threshold, and rbio 2.4 wavelet (Fig. 7). After the DWT denoising, signal on distance range 120–100 m can be easily distinguished from noise and as we can see the noise is closer to a straight line but still contains fragments, most likely of interference signals. Both signal and noise lost some energy after processing, but the result allowed us to gather typical fragments from a further distance than with the correlation methods.

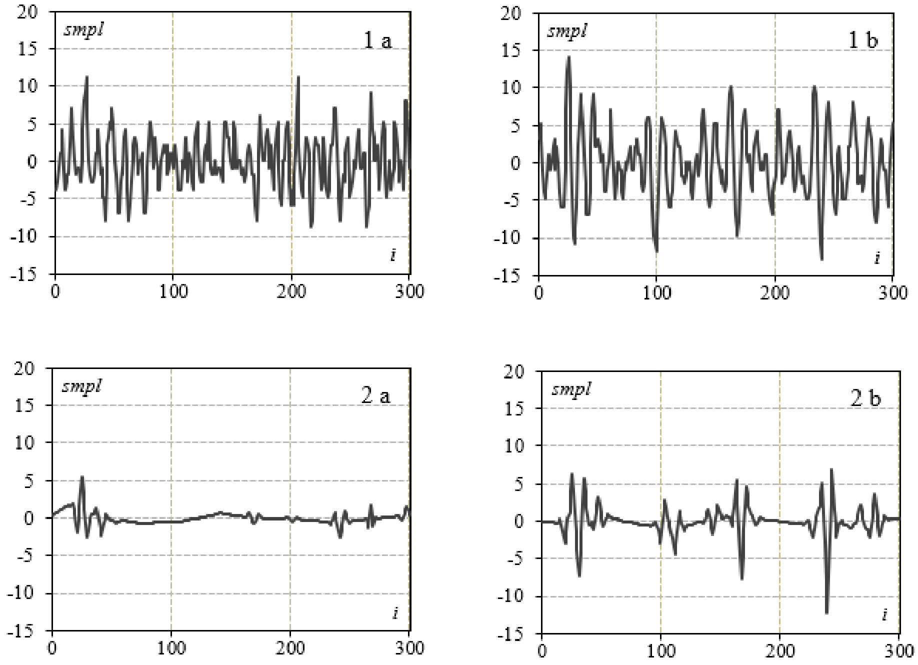

Figure 7. Denoising results of rbio2.4, soft threshold, L=5: 1 – input signal, 2 – denoised signal, a – noise, b – signal with typical fragments

More optimal in the calculation task was rbio3.3 for the hard threshold, which allows to use lower decomposition level to 3 levels, with still high improvement of average SNR through the set of signals. Selected denoising parameters lowered signal noise, highlighted existing typical samples, and even boosted its signal (Fig. 8). Signal hasn't improved a lot on 4 levels, noise energy lowered, but some signal interference fragments were boosted together with typical samples.

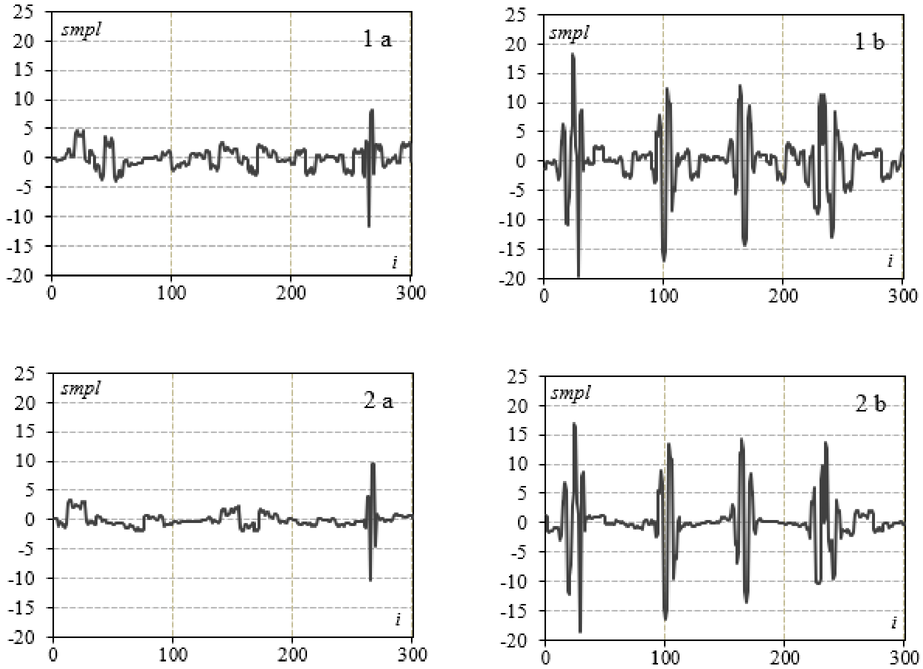

Figure 8. Denoising results of rbio3.3, hard threshold: 1 – L=3, 2 – L=4, a – noise, b – signal with typical fragments

Compared to the best parameters for soft threshold, we get a more noisy signal, with more prominent segments with signal interference, but what is more important energy of typical samples wasn't lowered, selected parameters even increased it, which potentially will improve search possibilities of the processed signal.

5. CONCLUSIONS

This study explored the efficiency of discrete wavelet transform (DWT) for denoising researched geo-signals, testing various configurations to determine optimal conditions. Specifically, we investigated the impact of different decomposition levels (ranging from 1 to 5), thresholding techniques (both hard and soft), and wavelet families, that include Haar, Daubechies, symlets, coiflets, biorthogonal, reverse biorthogonal, and discrete Meyer, on the denoising performance. The key conclusions drawn from this study are as follows:

1. The assumption that The DWT denoising method will provide worse results than correlation was disproven by the gathered results. It gave better denoising efficiency and processing results for further typical sample search tasks. The best correlation result gave us an improvement of SNR by 144.5%, while the best DWT denoising gave us the maximum result of 306% [14].
2. Further review of processed signals showed that less performance-heavy parameters, including hard threshold, rbio3.3 wavelet, and 3 decomposition levels, gave us better processing signal results than best-chosen parameters by average SNR improvement.
3. Evaluation of the DWT processing efficiency applied on non-stationary geo-signals requires an improved methodology to capture anomaly results and signal characteristics improvements. Average SNR provides denoising improvement evaluation but not potential improvement in typical fragments search possibilities.
4. Each parameter of the DWT denoising should only be reviewed with a combination of other parameters and not separately, because of the parameter's resonance to the signal characteristics, which can highlight either noise characteristics or signal characteristics, which may lead to a significant decrease or increase in efficiency.
5. A single parameter of the DWT denoising which showed some dynamics in efficiency change is the decomposition level, although it should be reviewed with connection to a specific wavelet.

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УДК 004.62

ОЦІНЮВАННЯ ЕФЕКТИВНОСТІ ЗАСТОСУВАННЯ МЕТОДУ ЗНЕШУМЛЕННЯ НА ОСНОВІ ДИСКРЕТНОГО ВЕЙВЛЕТ-ПЕРЕТВОРЕННЯ НА ІМПУЛЬСНИЙ СИГНАЛ З ГАРМОНІЙНИМИ СКЛАДОВИМИ

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Резюме. *Розглянуто проблему підбору параметрів для методу знешумлення на основі дискретного вейвлет-перетворення (DWT) при опрацюванні досліджуваного геосигналу з присутніми* *шумами різних типів та накладанні сторонніх сигналів та подальшого оцінювання ефективності застосування для пошуку повторюваних типових взірців сигналу. Проведено огляд теоретичного впливу параметрів досліджуваного методу знешумлення, існуючих методів підбору вейвлетів та рівнів декомпозиції, публікацій із застосування дискретного вейвлет перетворення для задач у різних сферах діяльності, теоретичної проблеми впливу збільшення рівнів декомпозиції на обчислювальну задачу для мікроконтролерів. Подано результати експериментального дослідження застосування методу знешумлення на основі дискретного вейвлет-перетворення на набір сигналів, записаних при натурних експериментах за різних середовищ поширення сигналу, у вигляді середньої зміни SNR опрацьованого сигналу до вхідного сигналу при визначених комбінаціях параметрів DWT методу знешумлення. Порівняння зміни результатів за різних рівнів декомпозиції продемонстрували як позитивну динаміку підвищення ефекитивності з певними вейвлетами, так і різкі падіння ефективності на певному рівні через фільтрацію типових взірців, що вказує на доцільність розгляду ефективності параметрів DWT знешумлення лише в окремих комбінаціях. Зафіксовано також різкі аномальні зростання чи падіння ефективності знешумлення конкретних сигналів через нестаціонарну природу сигналу та резонанс параметрів до шумів чи типових взірців, що потребує подальшого дослідження. За отриманими даними сформовано перелік найефективніших комбінацій параметрів для знешумлення досліджуваного геосигналу, подальший огляд яких, на можливість фіксації типових взірців з опрацьованих сигналів, показав доцільність використання оптимальнішої комбінації з трьома рівнями декомпозиції, твердим порогуванням та rbio3.3 вейвлетом, що окрім знешумлення та надання можливості фіксації типових фрагментів на відстані 120–100 м зберіг енергію сигналу та навіть посилив її.*

Ключові слова: *дискретне вейвлет-перетворення, DWT, шумоподавлення, опрацювання сигналів, нестаціонарний сигнал, імпульсний сигнал, геосигнал.*

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