

## Minimization of errors in discrete wavelet filtering of signals during ultrasonic measurements and testing

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### Abstract

Error minimizing methods for discrete wavelet filtering of ultrasonic meter signals are considered. For this purpose, special model signals containing various measuring pulses are generated. The psi function of the Daubechies 28 wavelet is used to generate the pulses. Noise is added to the generated pulses. A comparative analysis of the two filtering algorithms is performed. The first algorithm is to limit the amount of detail of the wavelet decomposition coefficients in relation to signal interference. The minimum value of the root mean square error of wavelet decomposition signal deviation which is restored at each level from the initial signal without noise is determined. The second algorithm uses a separate threshold for each level of wavelet decomposition to limit the magnitude of the detail coefficients that are proportional to the standard deviation. Like in the first algorithm, the task is to determine the level of wavelet decomposition at which the minimum standard error is achieved. A feature of both algorithms is an expanded base of discrete wavelets – families of Biorthogonal, Coiflet, Daubechies, Discrete Meyer, Haar, Reverse Biorthogonal, Symlets (106 in total) and threshold functions garrote, garrote, greater, hard, less, soft (6 in total). The model function uses random variables in both algorithms, so the averaging base is used to obtain stable results. Given features of algorithm construction allowed to reveal efficiency of ultrasonic signal filtering on the first algorithm presented in the form of oscillographic images. The use of a separate threshold for limiting the number of detail coefficients for each level of discrete wavelet decomposition using the given wavelet base and threshold functions has reduced the filtering error.

**Keywords:** ultrasonic measurements; testing; defectoscopy; ultrasonic pulse; interference; discrete wavelet filtering; wavelet decomposition; threshold function; detail coefficients; filtration error.

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### Introduction

Ultrasonic methods are widely used for measurements, testing and diagnostics [1] in various fields of industry. Recently, a number of new testing methods have appeared, which have significant economic advantages [2, 3] in comparison with traditional ultrasonic methods, for example, the possibility of contactless measurements and testing [1, 3, 4]. However, they usually have a lower sensitivity [1]. This issue requires the use of modern methods for processing the received information [5, 6]. One of the effective methods of dealing with noise is the method of discrete wavelet filtering [7–10].

A significant advantage of discrete wavelet filtering methods is its adaptive properties to the information component for the signal of an ultrasonic measuring device, which retains the noise component, which may exceed the informative component. The noise

component contains external noise, instrument interference, transducer interference and false signals. False signal pulses differ in spectrum and therefore create detail ratios that are limited by wavelet filtering.

In addition, a double frequency reduction at each level of signal wavelet decomposition provides a digital conversion of the analog signal according to the Nyquist criterion. That is, the sampling period should be half the period of the measuring signal.

Discrete wavelet transform of reflected signals, for example, from a defect, is dual, i.e. holds two components: high-frequency, which is responsible for the noise effect and is determined by the detail coefficients, and low-frequency, which is responsible for the signal information component and is determined by the approximation coefficients.

A number of publications are devoted to the use of discrete wavelet filtering in design of automated

ultrasonic meters and flaw detectors [7–10]. But all of them are based on a limited number of investigated wavelet functions, usually Daubechies, Symlet up to the 8<sup>th</sup> order and Coiflet up to the 5<sup>th</sup> order, as well as the hard and soft threshold functions. There is no unified approach to choosing the value of the very threshold for zeroing the wavelet detail coefficients. Comparison of filtering efficiency with a common threshold for all levels of wavelet decomposition and universal threshold for each level of wavelet decomposition has not been performed.

A significant contribution to the theory of discrete wavelet filtering was made by prof. Voskoboinikov Yu.Ye. with colleagues. In one of their recent articles, they considered the issues of wavelet filtering for noises of various statistical nature [11].

Considering the issue of creating an algorithm for minimizing wavelet filtering errors, especially for 1D signals, has not been fully resolved, it is advisable to increase the base of computational experiments by introducing additional wavelet and threshold functions using the PyWavelets library, which is highly specialized for DWT analysis [12]. The library is distributed under a free license from MIT with an expanded base of discrete wavelet and threshold functions, which made it possible to perform a full-fledged computational experiment.

### Brief theoretical information about wavelet filtering methods with general and universal thresholds

The discrete wavelet transform of a “pure” sample of a local measuring signal is determined by the relation [13]:

$$f(t) = \sum_k a_{j_0, k} \Phi_{j_0, k}(t) + \sum_{j=1}^J \sum_k d_{j_0, k} \Psi_{j_0, k}(t), \quad (1)$$

where:  $a_{j_0, k}, d_{j_0, k}$  – coefficients of approximation and detail of a non-noisy signal, respectively;  $\Phi_{j_0, k}(t), \Psi_{j_0, k}(t)$  – maternal and paternal wavelets, respectively;  $j_0, j, k$  – the initial and current levels of the wavelet decomposition and the serial number of the wavelet coefficient;  $f(t)$  – wavelet transform of a “pure” sample of a local measuring signal.

Discrete wavelet transform of a noisy signal is determined from the relation [13]:

$$\bar{f}(t) = \sum_k \bar{a}_{j_0, k} \Phi_{j_0, k}(t) + \sum_{j=1}^J \sum_k \bar{d}_{j_0, k} \Psi_{j_0, k}(t), \quad (2)$$

where:  $\bar{a}_{j_0, k}, \bar{d}_{j_0, k}$  – approximation and detail coefficients, respectively;  $\bar{f}(t)$  – wavelet transform function of a noisy signal.

DWT filtering of a noisy signal (2) is determined by the ratio:

$$\hat{f}(t) = \sum_k \bar{a}_{j_0, k} \Phi_{j_0, k}(t) + \sum_{j=1}^J \sum_k F(\lambda_j) \bar{d}_{j_0, k} \Psi_{j_0, k}(t), \quad (3)$$

where:  $F(\lambda_j)$  – threshold function, which is selected from the list garotte, garrote, greater, hard, less, soft, according to the condition of the minimum filtering error;  $\lambda_j$  – threshold at the  $j$ -th level of decomposition.

The universal threshold  $\lambda_j$  is determined from the ratio [13]:

$$\left. \begin{aligned} \sigma &= \frac{\text{median}(|d_{1,k}|)}{0,6742} \\ \lambda_j^{univ} &= \sigma \sqrt{2 \ln N_j} \end{aligned} \right\}, \quad (4)$$

where:  $\lambda_j^{univ}$  – universal threshold;  $N_j$  – the number of detail coefficients  $d_{j,k}$  at the  $j$ -th level of decomposition;  $\text{median}(|d_{1,k}|)$  – the median of the array  $|d_{1,k}|$  of detail coefficients at the first level.

We use the well-known ratio for the RMS filtering error in the time domain for “clean”  $f(t)$  and filtered  $\hat{f}(t)$  signals:

$$E = \frac{1}{N} \sum_{i=1}^N [f(t_i) - \hat{f}(t_i)]^2, \quad (5)$$

where  $t_i$  – countdown.

### Using the db28 “parent” wavelet function to simulate a model signal

To study the method of wavelet filtering of signals from ultrasonic flaw detectors, we will numerically simulate special functions by sweep type on oscilloscope (Fig. 1). Let us consider a simple example of a sweep containing pulses: probing, reflected from a defect, and bottom with additive noise overlay (Fig. 2), containing a mixture with a normal and logistic distribution of random numbers.

Using the numerical method, it is possible to set time intervals, signal attenuation in the material of the controlled sample, taking into account the nature of the defect and the type of ultrasonic wave. The article provides a simple example for demonstration.

### Implementation of two discrete wavelet filtering algorithms

For each complete cycle of a noisy signal decomposition (Fig. 2) transformed according to relation (2) to the maximum level, we choose a wavelet of Biorthogonal, Coiflet, Daubechies, Discrete Meyer, Haar, Reverse Biorthogonal, Symlets families, and threshold functions from the list of garotte, garrote, greater, hard, less, soft. With 106 wavelets and 6 threshold functions, we get 636 options. Considering the average number of levels of wavelet decomposition is 5, we have 3183 options for choosing the parameters. Since the noise is a random variable, it is necessary to average at least ten results, and finally we are provided with 31830 variants. Mixed random noise with normal and logistic distributions in equal proportions is to be used. The effect of noise on the filtering error for two values of the noise standard deviation (0.1; 0.2), comparing the results of the two algorithms, is to be investigated. According to the first algorithm proposed by the authors, marked (R), the number of detail

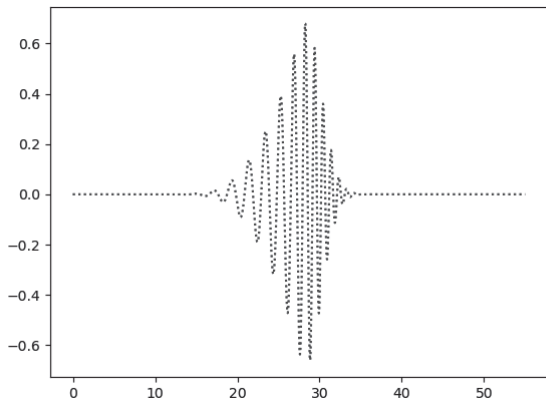


Fig. 1. Simulation of signal reflected from the defect by the db28 "parent" wavelet

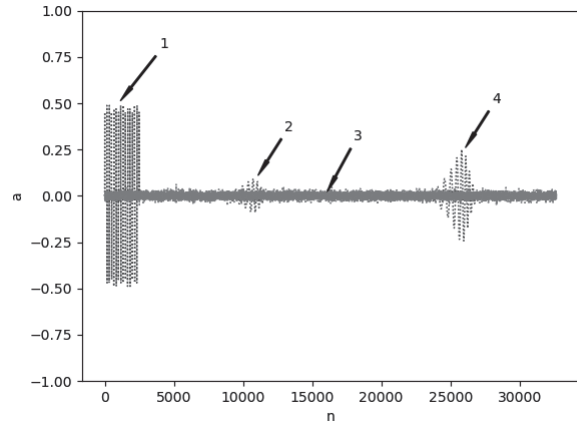


Fig. 2. Model function of the digitized sweep of the measurement pulses: a – relative amplitude; n – number of samples during digitizing; 1 – probing pulse; 2 – impulse reflected from the defect; 3 – additive noise; 4 – bottom impulse

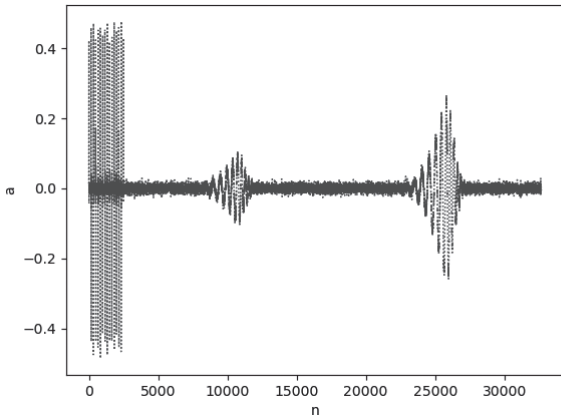


Fig. 3. R-filtered model signal for noise ( $\sigma = 0.1$ )

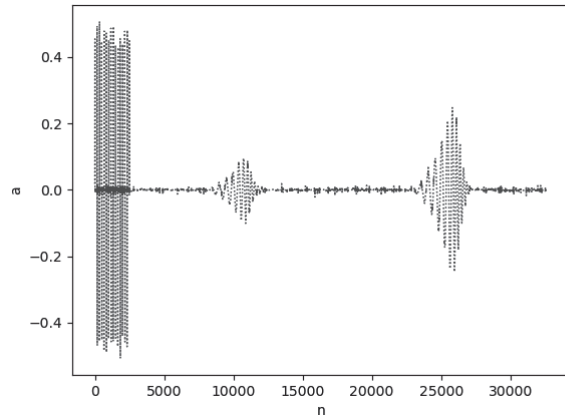


Fig. 4. UNIVER filtered model signal for noise ( $\sigma = 0.1$ )

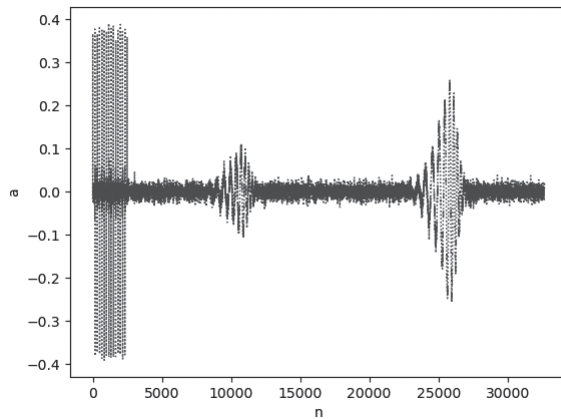


Fig. 5. R-filtered model signal for noise ( $\sigma = 0.2$ )

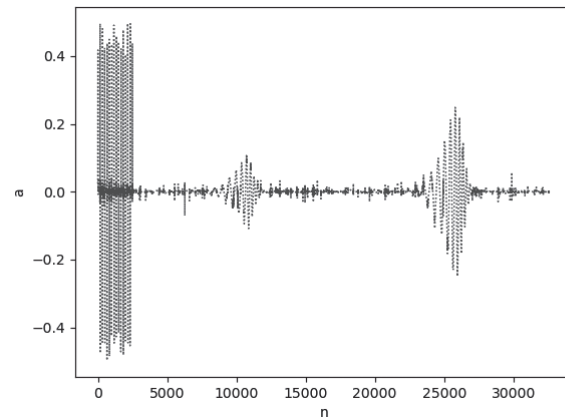


Fig. 6. UNIVER-filtered model signal for noise ( $\sigma = 0.2$ )

coefficients for all levels of DWT decomposition is reduced with the same threshold value, which is selected from the conditions for minimizing the filtering error. According to the second algorithm marked (UNIVER), which is the most used in practice, the threshold at each level of decomposition is calculated by relation (4) and decreases with each level of DWT decomposition. At each stage of the DWT decomposition, we need to determine the error according to (5) and compare the filtering results numerically considering the error and visually – using time base models (Fig. 3–6).

Data obtained from a numerical experiment: averaging base – 10; root-mean-square deviation of

noise 0.1; the average error of the R algorithm is -0.009% at the first level of the DWT decomposition; wavelet – db35; threshold function – garotte; the minimum error of 10 averaging is 0.009%; the general threshold is 0.8 for the garotte function.

Data obtained from a numerical experiment: averaging base – 10; root-mean-square deviation of noise 0.1; the average error of the UNIVER algorithm is -0.001% at the seventh level of DWT-decomposition; wavelet – bior2.6; threshold function – garotte; the minimum error of 10 averaging is close to zero; the threshold at the seventh level is 0.03 for the garotte function.

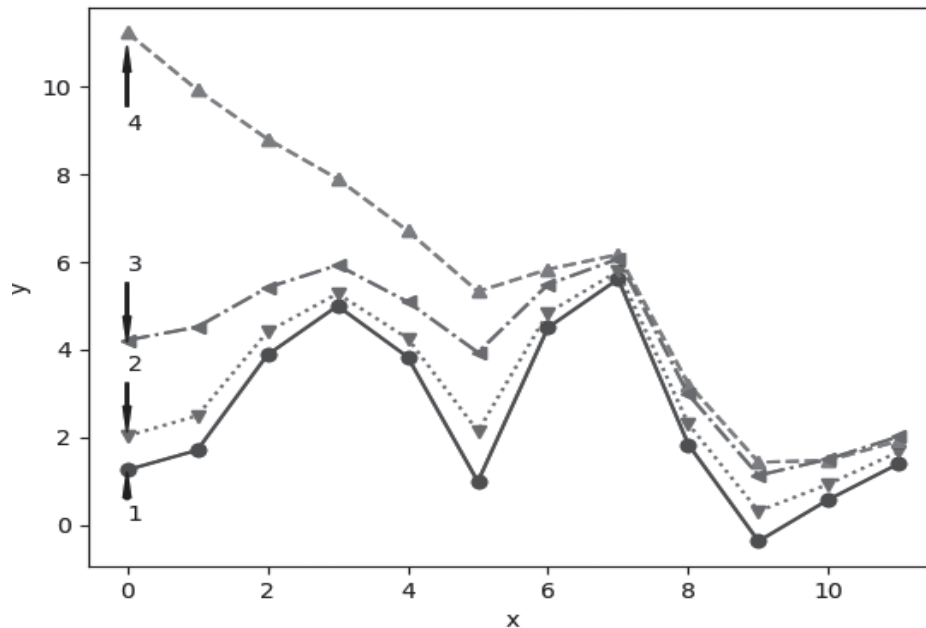


Fig. 7. Dependence of the logarithm of the sum of squares of the detail coefficients on the level  $j$  of the wavelet decomposition:  $y$  – logarithms of the sum of squared detail ratios  $\log \sum_{k \in Z} (d_{j,k})^2$ ;  $x$  – level  $j$  DWT; 1 – for a signal filtered by the R algorithm; 2 – for a signal filtered by the UNIVER algorithm; 3 – for a non-noisy signal; 4 – for a noisy signal

Data obtained from a numerical experiment: averaging base – 10; root-mean-square deviation of noise 0.2; the average error of the R algorithm is -0.019% at the second level of the DWT decomposition; wavelet – *coif17*; threshold function – *garotte*; the minimum error of 10 averaging is 0.019%; the general threshold is 0.8 for the *garotte* function. Data obtained from a numerical experiment: averaging base – 10; root-mean-square deviation of noise 0.2; the average error of the UNIVER algorithm is 0.002% at the seventh level of DWT decomposition; wavelet – *bior2.6*; threshold function – *garotte*; the minimum error of 10 averaging is 0.002%; the threshold at the seventh level is 0.06 for the *garotte* function.

Analyzing the results of calculations and Fig. 4–6, we can conclude that the UNIVER algorithm at the seventh level using the *bior2.6* wavelet and the *garotte* threshold function provides an error by an order of magnitude less than the R algorithm using the *coif17* wavelet and the *garotte* threshold function with a common threshold of 0.8.

#### Level distribution of the discrete wavelet decomposition of the sum of squares of the determination coefficients for the R and UNIVER algorithms

For each level of the wavelet decomposition, we use the relation for the sum of the squares of the detail coefficients  $d_{j,k}$  at the decomposition level  $j$ ;

$$s_j = \sum_{k \in Z} (d_{j,k})^2. \quad (6)$$

Using (6) and relations (1), (2), (3), (4), we construct a graph in a logarithmic scale for the levels of DWT decomposition for a pure signal, a signal with noise and signals filtered by two algorithms UNIVER and R (Fig. 7).

Analysis of the graph shows that the closest to the non-noisy signal 3 is the distribution 2 of the filtered signal according to the UNIVER algorithm. However, the signal compression according to the R algorithm at all decomposition levels is higher in the R algorithm.

#### Conclusions

A comparative analysis of the methods of discrete wavelet filtering of the generated oscillographic signal of ultrasonic flaw detection has been carried out. The high efficiency of the method has been determined with a separate threshold for each level of decomposition using the computational experiment method. A high-frequency wavelet of the Biorthogonal family and a *garotte* threshold function with nonlinearity in the restricted zones have been determined have been determined for the first time ever using the following specified method.

# Мінімізація похибок дискретної вейвлет-фільтрації сигналів при ультразвукових вимірюваннях і контролі

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## Анотація

Розглянуто методи мінімізації похибок дискретної вейвлет-фільтрації сигналів ультразвукових вимірювачів. Для цього генеруються спеціальні модельні сигнали, що містять різні вимірювальні імпульси. Для генерації імпульсів було використано функцію  $\psi$  вейвлета Daubechies 28. До згенерованих імпульсів додаються завади. Проведено порівняльний аналіз двох алгоритмів фільтрації. Перший полягає в обмеженні величини деталізації коефіцієнтів вейвлет-розкладання на перешкоди сигналу. При цьому визначалося мінімальне значення середньоквадратичної похибки відхилення вейвлет-розкладання сигналу, відновленого на кожному рівні, від початкового сигналу без шуму. Другий алгоритм використовує окремий для кожного рівня вейвлет-розкладання поріг обмеження величини деталізуючих коефіцієнтів, які пропорційні середньоквадратичному відхиленню. Як і в першому алгоритмі, завдання полягає у визначенні рівня вейвлет-розкладання, при якому досягається мінімальна середньоквадратична похибка. Особливістю обох алгоритмів є розширена база дискретних вейвлетів – це сімейства Biorthogonal, Coiflet, Daubechies, Discrete Meyer, Haar, Reverse Biorthogonal, Symlets (всього 106) і порогових функцій garotte, garrote, greater, hard, less, soft (всього 6). У модельній функції використовуються випадкові величини в обох алгоритмах, тому для отримання стабільних результатів застосовано базу усереднення. Наведені особливості побудови алгоритмів дозволили виявити ефективність фільтрації ультразвукових сигналів по першому алгоритму, поданих у вигляді осцилографічних зображень. Застосування окремого порога обмеження числа коефіцієнтів деталізації для кожного рівня дискретного вейвлет-розкладання із застосуванням наведеної бази вейвлет і порогових функцій знизило похибку фільтрації.

**Ключові слова:** ультразвукові вимірювання; контроль; дефектоскопія; ультразвуковий імпульс; завади; дискретна вейвлет-фільтрація; вейвлет-розкладання; порогова функція; коефіцієнти деталізації; похибка фільтрації.

# Минимизация погрешностей дискретной вейвлет-фильтрации сигналов при ультразвуковых измерениях и контроле

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## Аннотация

Минимизированы погрешности дискретной вейвлет-фильтрации ультразвуковых сигналов. Для этого генерируются комплексные импульсы. Для генерации импульсов была использована функция  $\psi$  вейвлета Daubechies 28. К импульсам добавляется шум. Проведен сравнительный анализ двух алгоритмов фильтрации. Первый состоит в ограничении величины детализирующих коэффициентов вейвлет-разложения зашумленного сигнала на всех уровнях разложения. Второй алгоритм использует отдельный для каждого уровня вейвлет-разложения порог ограничения величины детализирующих коэффициентов. Решена задача по определению уровня вейвлет-разложения, при котором достигается минимальная среднеквадратичная погрешность. Использована расширенная база дискретных вейвлетов – это семейства Biorthogonal, Coiflet, Daubechies, Discrete Meyer, Haar, Reverse Biorthogonal, Symlets и пороговых функций garotte, garrote, greater, hard, less, soft. В результате снижена погрешность вейвлет-фильтрации.

**Ключевые слова:** ультразвуковые измерения; ультразвуковой импульс; помехи; дискретная вейвлет-фильтрация; вейвлет-разложение; пороговая функция; коэффициенты детализации; погрешность фильтрации.

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