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A METHOD FOR ADAPTIVE WAVELET FILTERING OF SPEECH SIGNALS BASED ON DAUBECHIES FILTERS WITH MINIMIZATION OF ERRORS IN FINDING OPTIMAL THRESHOLDS

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Abstract—*The paper deals with the problem of adaptive wavelet filtering of speech signals based on Daubechies filters with minimization of errors in finding optimal threshold values. This approach is similar to estimating a speech signal by averaging it using a kernel that is locally adapted to the smoothness of the signal. In this case, a set of coupled mirror filters decomposes the speech signal in a discrete domain according to the orthogonal Daubechies wavelet basis into several frequency bands. Noise removal of speech signals is performed as a complete cutoff of the wavelet transform coefficients based on the assumption that their small amplitude values are noise. Thus, in the Daubechies wavelet basis, where coefficients with large amplitude correspond to abrupt changes in the speech signal, such processing preserves only the intermittent components originating from the input speech signal without adding other components caused by noise. In general, by equating small coefficients to zero, we perform adaptive smoothing that depends on the smoothness of the input speech signal. By keeping the coefficients of large amplitude, we avoid smoothing out sharp drops and preserve local features. Performing this procedure on several scales leads to a gradual reduction of the noise effect on both piecewise smooth and discontinuous parts of the speech signal. In view of this, the main task of the study is to adaptively generate micro-local thresholds, which will reduce the impact of additive noise on the pure form of the speech signal, and preserve significant wavelet coefficients of large amplitude that characterize the local features of the speech signal. Thus, as a result of our work, we have proved the feasibility of developing the presented method of wavelet filtering of speech signals with adaptive thresholds based on Daubechies wavelet analysis, which minimizes the loss of speech intelligibility and allows for noise removal depending on the properties and physical nature of the processed data.*

Index Terms—Speech signals; filtering of speech signals; adaptive wavelet filtering; wavelet transform; wavelet coefficients; thresholding of wavelet coefficients; optimal threshold values.

I. INTRODUCTION

Classical methods for cleaning speech signals from noise and extracting the true waveform are Fourier analysis methods. However, their insufficient ability to localize signal singularities and the need to introduce data windows in the time domain with subsequent spectrum blurring limits the use of Fourier analysis algorithms and causes a reasonable movement of speech signal processing practice and theory towards methods that provide better frequency and time resolution [1].

Daubechies wavelet functions are distinguished by the property of frequency-temporal localization of speech signals, have fast computing algorithms, and, in the conditions of non-stationarity of the analyzed speech signals and the presence of a forced background with unknown parameters, such as noise, are the most preferable basis for solving the problems of noise removal and restoration of the pure form of speech signals [2].

Cleaning speech signals from noise using Daubechies wavelet analysis is also a complex and challenging task. The basis of this class of methods is thresholding (trimming), which details the coefficients of the wavelet decomposition [3].

The threshold cutoff of the wavelet coefficients acts as a filter, and the choice of the quantization model, threshold value, and type of thresholding function is similar to the choice of filter characteristics [4].

Processing of the detail wavelet coefficients is based on the fact that the detail coefficients are spectral coefficients of the input speech signal and are of high-frequency nature. They localize small-scale changes in the speech signal not only in the time domain but also in the frequency domain [5].

The classical thresholding scheme for noise reduction has several drawbacks that significantly reduce the effectiveness of its application to non-stationary speech signals under uncertainty. Setting, for example, small values of the global threshold preserves the background components of the speech signal and leads to only a slight increase in the signal-to-noise ratio. At the same time, setting large threshold values entails the loss of wavelet coefficients, which can be important for restoring the cleaned form of the speech signal [6].

This circumstance is another argument in favor of using adaptive algorithms for speech signal denoising based on Daubechies wavelet analysis.

II. Literature Analysis and Problem Statement

The wavelet transformation of a short-term segment of a mathematically modeled speech signal $u(t)$ consists in its decomposition into a series by basic wavelet functions, which ensures the expansion of the corresponding spectrum by coordinate and frequency. To cover the entire speech signal with short wavelets, shift and scale transformation procedures are used. As a result, the speech signal is represented by a set of parametric wavelet functions that depend on frequency (scale) and coordinate (offset). Mathematically, this is expressed as follows [7], [8]:

$$u(t)=\frac{1}{a_0C_\psi}\int_{-\infty}^{\infty}db\int_{0}^{\infty}W\left(\frac{a}{a_0},\frac{b-b_0}{a_0}\right)\psi\left(\frac{t-b}{a}\right)\frac{da}{a^2},$$
$$W(a,b)=\frac{1}{a}\int_{-\infty}^{\infty}u(t)\psi\left(\frac{t-b}{a}\right)dt, \qquad (1)$$
$$C_\psi=\int_{-\infty}^{\infty}\left|\hat{\psi}(\omega)\right|^2\frac{d\omega}{|\omega|},$$

where $W(a,b)$ is the function that defines the wavelet spectrum, with the variables a and b setting the expansion and shift to cover the speech signal with wavelets; a_0, b_0 are control parameters that allow you to change the scale and move the image; C_ψ is the normalization factor; $\hat{\psi}(\omega)$ is the Fourier image of the base wavelet [9].

The noise-distorted speech signal is filtered by thresholding the wavelet spectrum:

$$W'(a,b)=W(a,b)\Phi\left(\left|W(a,b)\right|-f\right),$$
$$\Phi(x)=\begin{cases}1, & x>0\\ 0, & x\le 0\end{cases}, \qquad (2)$$

where $\Phi(x)$ is the Heavyside function, f is the noise reduction level.

After replacing $W(a,b)$ with $W'(a,b)$ in (1), a filtered speech signal is formed. Formulas (1) and (2) form the basis of the mathematical model of wavelet filtering of speech signals [10], [11].

The problem is to minimize the error of finding the optimal value of f in the task of filtering speech signals, which will reduce the risk of false zeroing of informative wavelet coefficients and thus prevent distortion of the speech signal during thresholding.

III. Proposed Method

The proposed method of adaptive wavelet filtering of speech signals based on Daubechies filters with minimization of errors in finding optimal thresholds is similar to the estimation of speech signals by averaging it with a kernel that is locally adapted to the smoothness of the signal. In this case, a set of coupled mirror filters decomposes the speech signal in a discrete domain according to the orthogonal Daubechies wavelet basis $\{\psi_{j,m}\}$ into several frequency bands.

To calculate the coefficients of the generating Daubechies wavelet filter of the n order, it is necessary to specify only the number of zero moments of the wavelet function N, that is, the order of the function is determined by the number of zero moments, and therefore $N=n$.

Then the calculation of the Daubechies wavelet filter is determined by the search for the coefficients of the polynomial

$$P_k=\frac{\prod_{i=-N+1}^{N}\left(\frac{1}{2}-i\right)}{\prod_{i=-N+1}^{N}(k-i)},\ k=1,\ \ldots,\ N\ ,$$

which for all values of $k\neq i$ form a vector $P=(P_N\ \ 0\ \ P_{N-1}\ \ 0\ \ldots\ 0\ \ P_1\ \ 1\ \ P_1\ \ 0\ \ P_2\ \ 0\ \ldots\ 0\ \ P_N)$, length $4N-1$ [12].

Then the vector of coefficients of the polynomial P is converted to the following form

$$P=\left(\frac{P_2}{P_1}\ \ \frac{P_3}{P_1}\ \ \cdots\ \ \frac{P_{4N-1}}{P_1}\right),$$

length $L=4N-2$.

Let's form a square matrix A of order L

$$A_L = \begin{pmatrix} -P_1 & -P_2 & \dots & -P_{L-1} & -P_L \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 & 0 \end{pmatrix},$$

where the first row of the matrix A_L defines the coefficients of the characteristic equation, which has the form

$$\lambda^L - P_1\lambda^{L-1} - P_2\lambda^{L-2} - \dots - P_{L-1}\lambda - P_L = 0,$$

where the roots $\lambda_{1,\dots,L}$ of this equation are the eigenvalues of the matrix A_L. The order of the square matrix A_L is always a multiple of two since $L = 4N - 2$.

By solving this equation using one of the numerical methods (half-division, combined, iteration, etc.), we find the roots $\lambda_{1,\dots,L}$ of this equation and thus form the vector λ of the eigenvalues of the matrix A_L

$$\lambda = (\lambda_1 \quad \dots \quad \lambda_L).$$

So, having a pre-formed vector of roots $\lambda_{1,\dots,J}$ of a polynomial, we calculate the vector of coefficients of this polynomial according to the expression

$$P_k = P_k - \lambda_j P_i,$$

where in cases where $j = 1, \dots, J$, then, $k = 2, \dots, j+1$, $i = 1, \dots, j$, and the initial values of the coefficients correspond to the vector

$$P = (P_1 \quad P_2 \quad \dots \quad P_{J+1}),$$

length $J + 1 = 2N$, where $P_1 = 1$, $P_{2,\dots,J+1} = 0$.

The normalization of the coefficients of the generating Daubechies wavelet filter of the n th order is carried out as follows

$$P_k = S_P \frac{P_k}{\sum_{k=1}^{2N} P_k},$$

where $k = 1, \dots, 2N$, forming the resulting vector of normalized coefficients

$$P = (P_1 \quad \dots \quad P_{2N}),$$

in such a way that the sum of the coefficients $\sum_{k=1}^{2N} P_k$ is equal to S_P, i.e. if $S_P = 1$, then $\sum_{k=1}^{2N} P_k = 1$.

Thus, the output of the above transformations is a vector of coefficients of the generating Daubechies wavelet filter of the n order, where the normalization procedure is applied [13].

Based on the analysis of existing publications, it is advisable to use the generating Daubechies wavelet function of at least the 12th order, i.e., $N = 12$, as derived values P of the coefficients of the Daubechies wavelet filter in speech signal filtering tasks, which is confirmed by the graph of cumulative sums in Fig. 1 (b).

Below are the coefficients of the 18th-order Daubechies generating wavelet filter and its cumulative sums of the squares of the coefficients found using the above algorithm (Fig. 1).

Notice how fast the cumulative sum of the Daubechies filter grows (Fig. 1b).

This is because its energy is concentrated on small abscissa. Since the Daubechies wavelet has an extreme phase, the cumulative sum of its coefficient squares grows at a rapid rate, which makes this family of wavelet filters attractive for use in speech signal processing tasks.

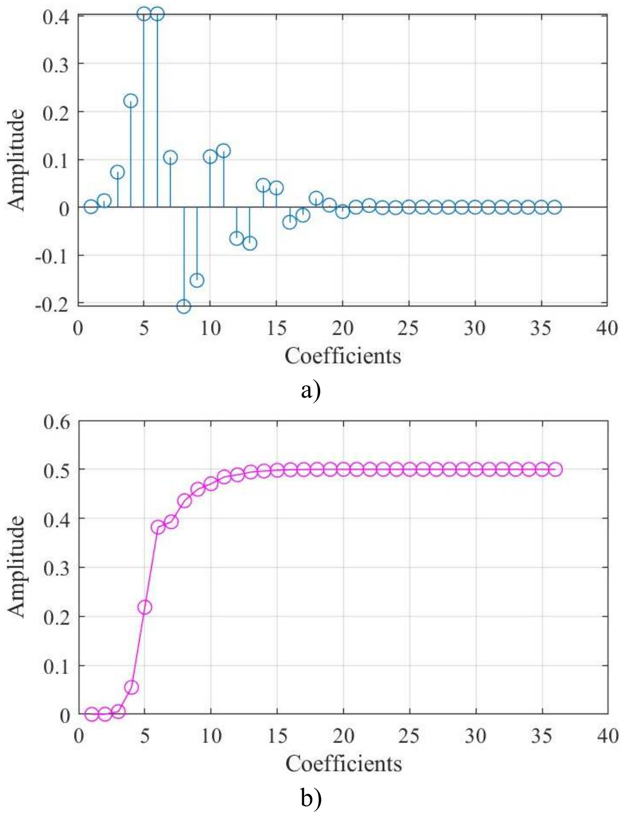


Fig. 1. The coefficients of the generating Daubechies wavelet filter of the 18th order (a) and its cumulative sums of squares of coefficients (b)

Then let's calculate the coefficients of the orthogonal wavelet filters based on the values of the coefficients of the Daubechies generating wavelet filter of the n order found earlier [14].

Thus, the coefficients of the orthogonal Daubechies low-pass wavelet filter for the inverse discrete wavelet transform are determined as follows

$$R = \sqrt{2}\left(P_1 \quad \dots \quad P_{2N}\right),$$

of length $2N$, then the coefficients of the orthogonal low-pass Daubechies wavelet filter for the direct discrete wavelet transform are determined by

$$D = \left(R_{2N} \quad \dots \quad R_1\right),$$

corresponding to the inversion of the coefficients R.

The coefficients of the orthogonal Daubechies high-pass wavelet filter for the inverse discrete wavelet transform are determined by calculating the quadrature-mirror filter as follows

$$W = \left(R_{2N} - R_{2N-1}R_{2N-2} - R_{2N-3} \dots - R_4R_3 - R_2R_1\right),$$

then the coefficients of the orthogonal Daubechies high-pass wavelet filter for the direct discrete wavelet transform are determined by

$$V = \left(W_{2N} \quad \dots \quad W_1\right),$$

corresponding to the inversion of the coefficients W.

Thus, we obtained the vectors of values D and V, as well as R and W, which correspond to the coefficients of the orthogonal Daubechies low-pass and high-pass wavelet filters for the direct and inverse discrete wavelet transform.

As an example, let's show the coefficients of orthogonal wavelet filters based on the 18th-order Daubechies generating wavelet filter found by the above method (Fig. 2).

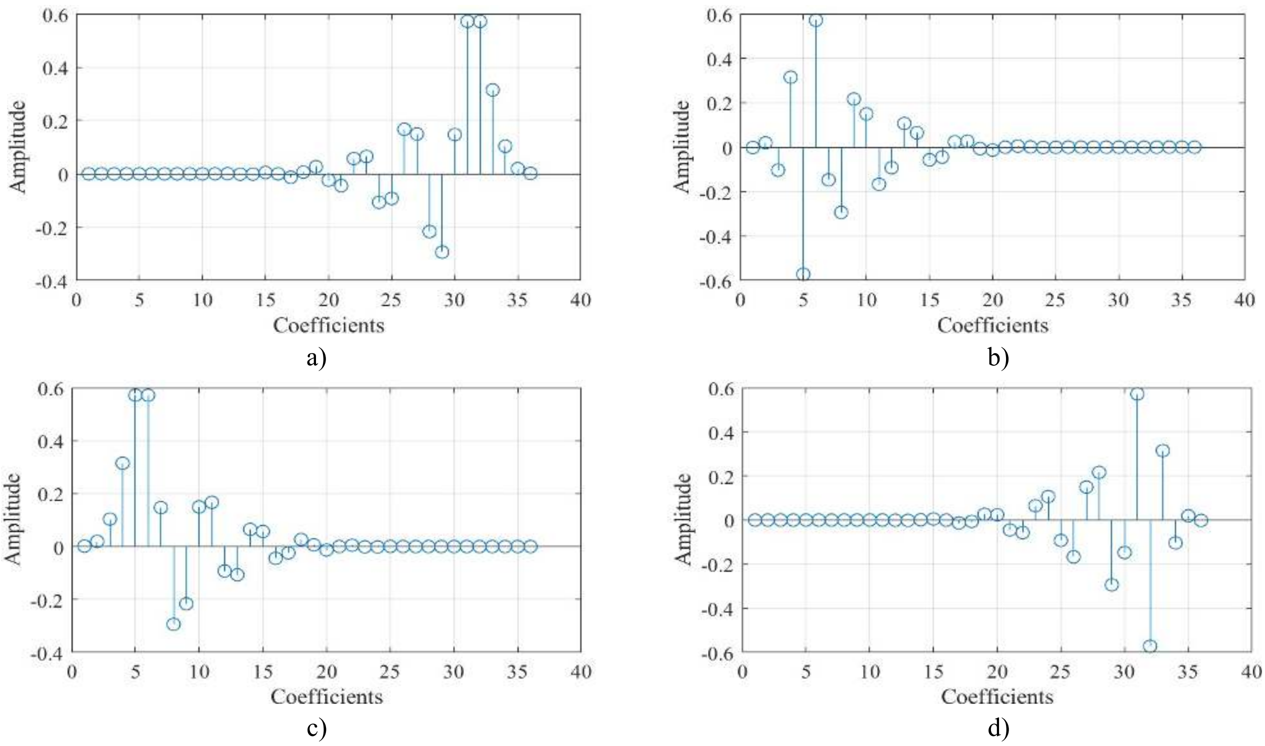


Fig. 2. Coefficients of orthogonal Daubechies wavelet filters of the 18th order
(a) is low-pass decomposition filter D, (b) is high-pass decomposition filter V,
(c) is low-pass reconstruction filter R, (d) is high-pass reconstruction filter W

Since the speech signal is a non-stationary random process, it was proposed to use a discrete wavelet transform to process it, which receives samples of the speech signal as input and generates wavelet coefficients as output [15].

Let us turn to the diagram shown in Fig. 3a. The speech signal $f(k)$ is fed to the low-pass filter D and the high-pass filter V Daubechies, where convolution (digital filtering) is calculated according to the formula:

$$y(k) = \sum_{l=0}^{2n-1} f(k)q(k-l),$$

where $2n$ is the number of samples of the impulse response of the Daubechies wavelet filter $q(k)$. Accordingly, the output of the filters will be the high-frequency $y_H(k)$ and low-frequency $y_L(k)$ components of the speech signal. During the transition from the current level of wavelet decomposition to the next, decimation $\downarrow 2$ with a factor of 2 is performed, i.e., thinning the signals at the filter output by half, after which the wavelet coefficients of approximation a_1 and detail d_1 are formed.

At the next level of decomposition, instead of the speech signal $f(k)$, the wavelet coefficients of approximation a_1 are fed to D and V, while the wavelet coefficients of detail d_1 remain unchanged.

The scheme shown in Fig. 3b performs wavelet reconstruction of the speech signal. This procedure uses interpolation operations $\uparrow 2$ and filtering with Daubechies reconstruction filters R and W. The interpolation operation with factor 2, the inverse of decimation with factor 2, is performed by doubling the number of components by adding zero components.

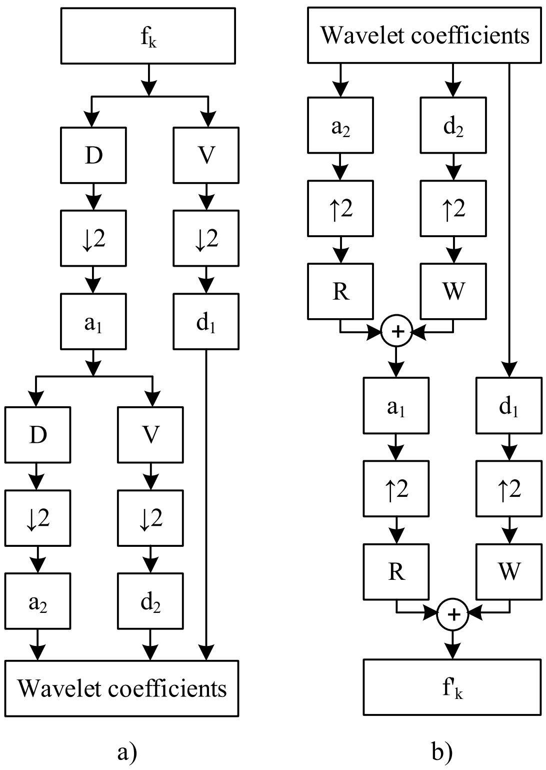


Fig. 3. Scheme of wavelet transform based on Daubechies frequency filtering: (a) is decomposition algorithm, (b) is reconstruction algorithm

When $\oplus$ adds up the signals received at the output of R and W at all levels, the speech signal is reconstructed at the original level.

Noise reduction of speech signals is performed as a complete cutoff of the wavelet transform coefficients based on the assumption that their low-amplitude values are noise.

Thus, in the Daubechies wavelet basis, where coefficients with large amplitudes correspond to abrupt changes in the speech signal, such processing preserves only the intermittent components originating from the input speech signal without adding other components caused by noise.

In general, by equating small coefficients to zero, we perform adaptive smoothing that depends on the smoothness of the input speech signal $f(t)$. By keeping the coefficients of large amplitude, we avoid smoothing out sharp drops and preserve local features. Performing this procedure on several scales leads to a gradual reduction of the noise effect on both piecewise smooth and discontinuous parts of the speech signal.

Each speech signal represented in a discrete form has a certain percentage of significant wavelet coefficients $\langle f, \psi_{j,m} \rangle$, which increases with the scale of wavelet decomposition a^j. This fact is explained by the fact that the low-frequency component of the speech signal generates a smaller number of wavelet coefficients of large amplitude, while the number of wavelet coefficients of the high-frequency component of the speech signal with small amplitude increases at the levels. If the value of a^j is large, the threshold T should be increased to filter out the wavelet coefficients of small amplitude at all levels of decomposition [16].

Thus, to solve the problem of adaptive noise removal, it is necessary to perform adaptive generation of micro-local thresholds, which will reduce the effect of additive noise on the pure form of the speech signal, and preserve significant wavelet coefficients of large amplitude that characterize the local features of the speech signal.

Let us represent the model of the speech signal $f(t)$ distorted by additive noise as

$$X(t) = f(t) + \eta(t). \tag{3}$$

Then, when such a signal is decomposed by a set of conjugate mirror filters on a discrete orthogonal Dobeschy basis $\{\psi_m\}$ gives:

$$WX[m] = \langle X, \psi_m \rangle,$$
$$Wf[m] = \langle f, \psi_m \rangle, \ ,$$
$$W\eta[m] = \langle \eta, \psi_m \rangle.$$

The scalar product (1) from ψ_m gives

$$WX[m] = Wf[m] + W\eta[m].$$

This means that the noise model does not depend on the decomposition basis and remains the same in it as in the input speech signal.

Let's introduce a linear operator D that evaluates $Wf[m]$ against $WX[m]$ using the function $d_m(x)$. The resulting estimate is

$$\widetilde{F} = DX = \sum_{m=0}^{N-1} d_m(WX[m])\psi_m.$$

When $d_m(x)$ is a threshold function, the risk of this assessment can be minimized.

Threshold filtering is performed using a threshold function (Fig. 4), which is set as follows:

$$d_m(x) = \rho_T(x) = \begin{cases} x, & \text{if } |x| > T, \\ 0, & \text{if } |x| \le T, \end{cases}$$

and removes all wavelet coefficients whose amplitude is below the set threshold T.

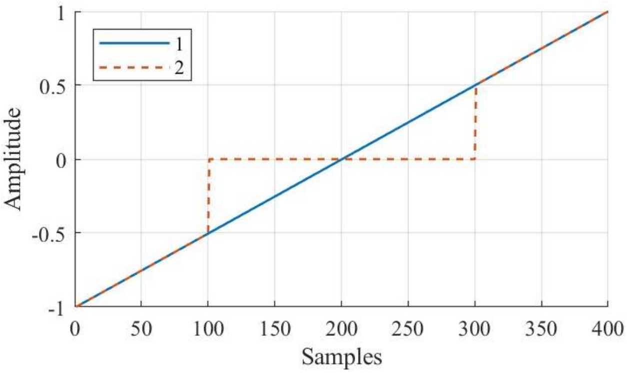


Fig. 4. Graphs of linear dependence (1 is line in blue) and threshold function (2 is line in red)

In the Daubechies wavelet basis, the coefficients of large amplitude correspond to discontinuities in the speech signal and its abrupt changes. This means that the estimation preserves only irregular components that originate from the input speech signal in the decomposition, without adding parasitic bursts caused by noise.

The threshold should be chosen adaptively and be slightly larger than the maximum noise level. That is, the values of $|W\eta[m]|$ should be more likely to be less than T. This is how the minimum risk level in threshold wavelet filtering of speech signals is achieved [17].

Let $r_t(x,T)$ be the risk of the threshold estimate computed with the threshold T. Then the estimate $\tilde{r}_t(x,T)$ of the risk $r_t(x,T)$ should be calculated from the speech signal $X(t)$, which is distorted by noise. The value of the threshold T in this case is optimized by minimizing $\tilde{r}_t(x,T)$.

To find the value of $\tilde{T}$ that minimizes the estimate of $\tilde{r}_t(x,T)$, N of the coefficients of the data $WX[m]$ are sorted by decreasing amplitude. Then, the wavelet decomposition coefficients ranked in this way form an ordered set $\{WX^r[k]\}_{1\le k\le N}$, where any $WX^r[k] = WX[m_k]$ is the corresponding coefficient of rank k:

$$\left|WX^r[k]\right| \ge \left|WX^r[k+1]\right|.$$

Let l be some index such that $\left|WX^r[l]\right| \le T < \left|WX^r[l-1]\right|$, then we can assume

$$\tilde{r}_t(f,T) = \sum_{k=1}^{N} \left|WX^r[k]\right|^2 - (N-l)\sigma^2 + l(\sigma^2 + T^2), \quad (4)$$

where σ^2 is the variance of the noise component.

Then to minimize $\tilde{r}_t(x,T)$, you must choose $T = \left|WX^r[l]\right|$.

The variance σ^2 of the noise $\eta[n]$ can be determined from the data in (3), for which it is necessary to suppress the influence of $f[n]$, such a rough estimate can be made using the average values of the wavelet coefficients of the smallest scale.

This statement is due to the fact that at each level of the wavelet decomposition of the input speech signal $X(t)$ of length N, the set of values $\{\langle X,\psi_m\rangle\}_{0\le m\le N/2}$ is finite and has only a few coefficients of large amplitude. Therefore, for most parts of $\langle X,\psi_m\rangle \approx \langle \eta,\psi_m\rangle$ [18].

Then, if M_X is the median of the set $\{|\langle X,\psi_m\rangle|\}_{0\le m\le N/2}$, then a rough estimate of the variance σ^2 of the noise η is estimated by M_X, neglecting the influence of $f[n]$:

$$\tilde{\sigma} = \frac{M_X}{0,6745}. \quad (5)$$

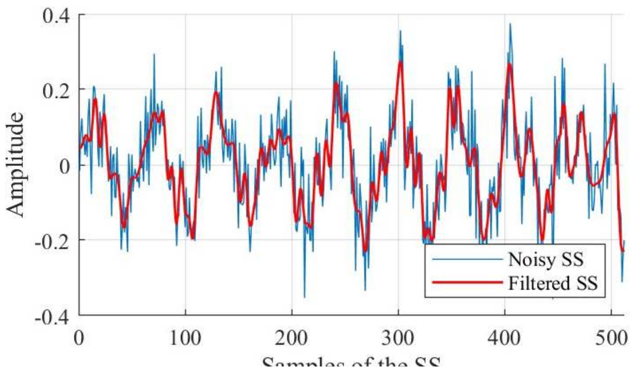
Next, we show the results of modeling the proposed method of adaptive wavelet filtering of speech signals based on Daubechies filters with minimizing errors in finding optimal thresholds (Fig. 5).

Thus, the adaptive noise reduction procedure based on wavelet decomposition coefficients can be performed as follows:

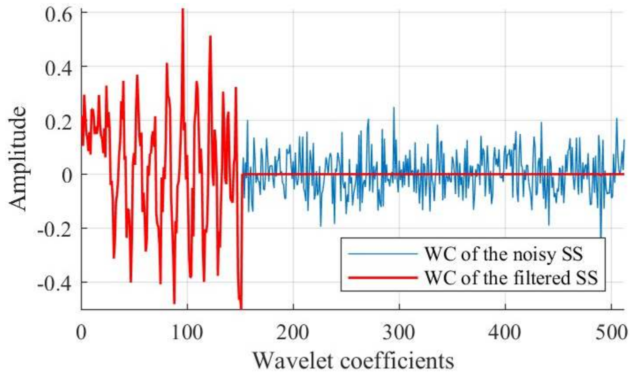
1) Calculating the estimate $\tilde{\sigma}^2$ of the noise variance σ^2 using the median formula (5) at the smallest scale of decomposition;

2) Calculating the threshold T_j for each level of decomposition j with risk minimization (4);

3) Thresholding of the wavelet decomposition coefficients by the obtained threshold for each scale level a^j.



a)



b)

Fig. 5. Wavelet filtering of a speech signal (SS) by adaptive thresholding: noisy and filtered SS (a), wavelet coefficients (WC) of noisy and filtered SS (b)

IV. Conclusions

Threshold processing of speech signals can be further adapted to the data if the method proposed above is applied not to all wavelet coefficients of the analyzed level, but to its individual sections, i.e., selected segments. In the same way, the block scheme of thresholding can be reduced to a micro-local scheme, in which the threshold is generated for each wavelet coefficient separately.

As an additional stage of optimization of the proposed method of speech signal denoising under uncertainty, we can use the estimation of losses incurred at this stage. The use of the loss estimate will allow controlling the limits of change in threshold values both for the entire speech signal and within individual segments. It is proposed to use normalized or peak root mean square estimates, root mean square error, or signal-to-noise ratio as such estimates.

Thus, as a result of the work carried out, we have proved the feasibility of developing the above method of wavelet filtering of speech signals with adaptive thresholds based on Daubechies wavelet analysis, which minimizes the loss of speech intelligibility and allows for noise removal depending on the properties and physical nature of the data being processed. We also propose an algorithm that performs adaptive noise removal based on the above method, and suggest ways to control the method, ways to modify it, and further improve its efficiency.

References

[1] A. Aslam, Z. Khalid and J. D. McEwen, “Multiscale Optimal Filtering on the Sphere,” in *IEEE Signal Processing Letters*, vol. 28, pp. 394–398, 2021. https://doi.org/10.1109/LSP.2021.3056236

[2] I. K. Alak and S. Ozaydin, “Speech Denoising with Maximal Overlap Discrete Wavelet Transform,” *2022 International Conference on Electrical and Computing Technologies and Applications (ICECTA)*, Ras Al Khaimah, United Arab Emirates, 2022, pp. 27–30. https://doi.org/10.1109/ICECTA57148.2022.9990250

[3] G. Yang, Y. Song and J. Du, “Speech Signal Denoising Algorithm and Simulation Based on Wavelet Threshold,” *2022 4th International Conference on Natural Language Processing (ICNLP)*, Xi'an, China, 2022, pp. 304–309. https://doi.org/10.1109/ICNLP55136.2022.00055

[4] Z. Yan, H. Yan and T. Wang, “A fast non-local means filtering method for interferometric phase based on wavelet packet transform,” in *Radio Science*, vol. 56, no. 6, pp. 1–14, June 2021. https://doi.org/10.1029/2019RS007052

[5] E. Özen and N. Özkurt, “Speech Noise Reduction with Wavelet Transform Domain Adaptive Filters,” *2021 Global Congress on Electrical Engineering (GC-ElecEng)*, Valencia, Spain, 2021, pp. 15–20. https://doi.org/10.1109/GC-ElecEng52322.2021.9788190

[6] R. Fu, J. Zhang, R. Wang and T. Xu, “Improved Wavelet Thresholding Function and Adaptive Thresholding for Noise Reduction,” *2023 11th International Conference on Intelligent Computing and Wireless Optical Communications (ICWOC)*, Chongqing, China, 2023, pp. 25–30. https://doi.org/10.1109/ICWOC57905.2023.10200530

[7] X. Pan, L. Zhang and H. Huang, “Harmonic Cancellation by Adaptive Notch Filter Based on Discrete Wavelet Packet Transform for an MMCC-STATCOM,” in *IEEE Transactions on Power Delivery*, vol. 37, no. 3, pp. 1834–1844, June 2022. https://doi.org/10.1109/TPWRD.2021.3099201

[8] X. Li and S. Yin, “Speech Denoising Based on Wavelet Transform of Correlation Function,” *2021 International Conference on Electronic Information Technology and Smart Agriculture (ICEITSA)*, Huaihua, China, 2021, pp. 27–30. https://doi.org/10.1109/ICEITSA54226.2021.00015

[9] K. Sun, Y. Lu, L. Huang, X. Chen, X. Zhang and S. He, “Wavelet denoising method based on improved threshold function,” *2022 IEEE 10th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, Chongqing, China,

2022, pp. 1402–1406. https://doi.org/10.1109/ITAIC54216.2022.9836698

[10] H. Wu *et al.*, “The Improved Wavelet Denoising Scheme Based on Robust Principal Component Analysis for Distributed Fiber Acoustic Sensor,” in *IEEE Sensors Journal*, vol. 23, no. 19, pp. 22944–22951, 1 Oct.1, 2023. https://doi.org/10.1109/JSEN.2023.3305532

[11] O. Julius, I. C. Obagbuwa, A. A. Adebiyi and E. B. Michael, “Implementation of Audio Signals Denoising for Perfect Speech-to-Speech Translation Using Principal Component Analysis,” *2023 International Conference on Science, Engineering and Business for Sustainable Development Goals (SEB-SDG)*, Omu-Aran, Nigeria, 2023, pp. 1–6. https://doi.org/10.1109/SEB-SDG57117.2023.10124385

[12] D. Bakhtiiarov, G. Konakhovych and O. Lavrynenko, “Protected system of radio control of unmanned aerial vehicle,” *2016 4th International Conference on Methods and Systems of Navigation and Motion Control (MSNMC)*, Kyiv, Ukraine, 2016, pp. 196–199. https://doi.org/10.1109/MSNMC.2016.7783141

[13] O. Lavrynenko, G. Konakhovych and D. Bakhtiiarov, “Method of voice control functions of the UAV,” *2016 4th International Conference on Methods and Systems of Navigation and Motion Control (MSNMC)*, Kyiv, Ukraine, 2016, pp. 47–50. https://doi.org/10.1109/MSNMC.2016.7783103

[14] D. I. Bakhtiiarov, G. F. Konakhovych and O. Y. Lavrynenko, “An Approach to Modernization of the Hat and COST 231 Model for Improvement of Electromagnetic Compatibility in Premises for Navigation and Motion Control Equipment,” *2018 IEEE 5th International Conference on Methods and Systems of Navigation and Motion Control (MSNMC)*, Kyiv, Ukraine, 2018, pp. 271–274. https://doi.org/10.1109/MSNMC.2018.8576260

[15] O. Lavrynenko, A. Taranenko, I. Machalin, Y. Gabrousenko, I. Terentyeva and D. Bakhtiiarov, “Protected Voice Control System of UAV,” *2019 IEEE 5th International Conference Actual Problems of Unmanned Aerial Vehicles Developments (APUAVD)*, Kyiv, Ukraine, 2019, pp. 295–298. https://doi.org/10.1109/APUAVD47061.2019.8943926

[16] O. Lavrynenko, R. Odarchenko, G. Konakhovych, A. Taranenko, D. Bakhtiiarov and T. Dyka, “Method of Semantic Coding of Speech Signals based on Empirical Wavelet Transform,” *2021 IEEE 4th International Conference on Advanced Information and Communication Technologies (AICT)*, Lviv, Ukraine, 2021, pp. 18–22. https://doi.org/10.1109/AICT52120.2021.9628985

[17] R. Odarchenko, O. Lavrynenko, D. Bakhtiiarov, S. Dorozhynskyi and V. A. O. Zharova, “Empirical Wavelet Transform in Speech Signal Compression Problems,” *2021 IEEE 8th International Conference on Problems of Infocommunications, Science and Technology (PIC S&T)*, Kharkiv, Ukraine, 2021, pp. 599–602. https://doi.org/10.1109/PICST54195.2021.9772156

[18] V. Kuzmin, M. Zaliskyi, O. Holubnychyi and O. Lavrynenko, “Empirical Data Approximation Using Three-Dimensional Two-Segmented Regression,” *2022 IEEE 3rd KhPI Week on Advanced Technology (KhPIWeek)*, Kharkiv, Ukraine, 2022, pp. 1–6. https://doi.org/10.1109/KhPIWeek57572.2022.9916335

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О. Ю. Лавриненко, Д. І. Бахтіяров, Г. Ф. Конахович, В. Є. Курушкін. Метод адаптивної вейвлет-фільтрації мовних сигналів на основі фільтрів Добеші з мінімізацією помилок знаходження оптимальних порогових значень

У статті розглядається проблематика адаптивної вейвлет-фільтрації мовних сигналів на основі фільтрів Добеші з мінімізацією помилок знаходження оптимальних порогових значень. Даний підхід аналогічний оцінюванню мовного сигналу шляхом його усереднення за допомогою ядра, яке локально адаптоване до гладкості сигналу. Набір сполучених дзеркальних фільтрів у такому разі розкладає мовний сигнал у дискретній області по ортогональному вейвлет-базису Добеші на кілька частотних діапазонів. Шумоочищення мовних сигналів виконується як повне відсікання коефіцієнтів вейвлет-перетворення виходячи з припущення, що їх значення малої амплітуди і є шум. Таким чином, у вейвлет-базисі Добеші, де коефіцієнти з великою амплітудою відповідають різким змінам мовного сигналу, така обробка зберігає лише переривчасті складові, що походять від вхідного мовного сигналу без додавання інших компонентів, обумовлених шумом. Загалом, прирівнюючи малі коефіцієнти нулю, ми виконуємо адаптивне згладжування, що залежить від гладкості вхідного мовного сигналу. Зберігаючи коефіцієнти великої амплітуди, ми уникаємо згладжування різких перепадів та зберігаємо локальні особливості. Проведення такої процедури на кількох масштабах веде до поступового зменшення впливу шуму як на кусочно-гладких, так і на розривних ділянках мовного сигналу. Зважаючи на це, головне завдання дослідження полягає у адаптивній генерації мікролокальних порогів, що дозволить зменшити вплив адитивного шуму на чисту форму мовного сигналу, і зберегти значущі вейвлет-коефіцієнти великої амплітуди, які характеризують локальні особливості мовного сигналу. Таким чином, в результаті проведеної роботи було доведено доцільність розробки представленого методу вейвлет-фільтрації мовних сигналів адаптивними порогами на основі вейвлет-аналізу Добеші, що мінімізує втрати розбірливості мовних сигналів і дозволяє проводити операцію шумоочищення залежно від властивостей та фізичної природи даних, що обробляються.
Ключові слова: мовні сигнали; фільтрація мовних сигналів; адаптивна вейвлет-фільтрація; вейвлет-перетворення; вейвлет-коефіцієнти; порогова обробка вейвлет-коефіцієнтів; оптимальні значення порогів.

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