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SELECTION OF DELTA FUNCTION WAVEFORM AND ITS PARAMETERS FOR OPTIMAL DISCRETE WAVELET TRANSFORM APPLICATION TO INPUT SIGNALS BASED ON THEIR PURPOSE

Qalandarov Jo'rabek To'khtamirzayev 1
Khakimov Ilhomjon Olimjon oglu 1
Tohirjonova Muattarkhon Rasuljon qizi 1
Ahmadjonova Madinabonu Khasanboy qizi 1
Sharipbayev Sobitkhon Sobir oglu 2
Reutskaya Olga Gennadievna 3
1 Namangan State University
2 Namangan State Technical University
3 Belarusian National Technical University

Abstract
The discrete wavelet transform (DWT) stands out as one of the most powerful techniques for analyzing non-stationary signals across time and scale domains. Sensor signals like vibration, acoustic, current-voltage, medical (ECG/EEG), and others captured in real-world systems typically feature noise, transient events (impulses, jumps, discontinuities), and gradual trends. Thus, selecting the appropriate wavelet type and its parameters during processing critically determines the output's precision and reliability.

This paper thoroughly examines optimal DWT deployment tailored to input signal objectives, focusing on parameter tuning methods—including wavelet choice, decomposition levels, thresholding, and boundary handling for impulse-like (delta) events. It also introduces a unified selection algorithm grounded in energy compaction, symmetry, vanishing moments, and phase distortion metrics for diagnostic and detection applications. Ultimately, it provides practical

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guidelines for noise suppression, transient event isolation, and robust feature extraction via DWT.

Keywords: Discrete wavelet transform, wavelet selection, impulse (delta), denoising, threshold, decomposition level, feature extraction, compression, diagnostics.

Introduction

Signals received in industrial and scientific-practical systems often have a complex structure and unstable spectral composition. This is due to the fact that in real processes, factors such as load changes, mechanical shock, switching of operating modes, contact breaks or electromagnetic noise act simultaneously. In such conditions, assessing the signal only by the average frequency content is often not enough. Because in the task of diagnostics or event detection, the question "what happened at what time" is of primary importance. Discrete wavelet transform satisfies this need, since it analyzes the signal in local segments in time at different scales. As a result, short-duration pulses and sharp changes (near-delta events) are more clearly visible. At the same time, DTT is computationally fast and works well on digital devices.

The effectiveness of wavelet methods largely depends on the correctly selected wave function and its parameters. If the wavelet does not match the nature of the signal, then as a result of the transformation, useful components can be suppressed along with noise. For example, if a wavelet with a very "smooth" and long base is selected for detecting impulse events, the impulse energy will be spread out by several factors and detection will become difficult. On the contrary, if a wavelet with a very short base is used for smooth biological signals (ECG), there is a possibility of increasing the reconstruction error or causing shape distortion. Therefore, "optimal selection" means finding the most optimal wavelet among the wavelets according to the criteria suitable for the purpose. This process should be carried out based on experimental tests, metrics and theoretical properties. The resulting selection can significantly reduce noise, compress or increase the accuracy of classification.

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The main purpose of this article is to describe a systematic method for selecting DTT parameters according to the purpose of processing the received signals. In this case, special attention is paid to the issue of wavelet selection for events close to delta (impulse). Since impulses are often the first sign of a malfunction, their early detection improves the maintenance strategy. The article explains the criteria for wavelet selection such as localization, symmetry, vanishing moments, orthogonality and energy compaction. The influence of the decomposition level, threshold type and boundary processing on the result is also explained in detail. A general algorithm is also presented in the form of practical steps. Finally, typical errors and recommendations for their elimination are given.

2. Basics of Discrete Wavelet Transform (DWT)

Discrete wavelet transform is based on the idea of multi-scale analysis of the signal, that is, the signal is divided into large (low frequency) and small (high frequency) structures. In digital form, this process is carried out through filter banks. The signal is first passed through a low-pass filter, and the "approximation" part is obtained. Then, the "detail" part is separated through a high-pass filter. After each stage, the number of samples is halved, which increases the calculation speed. Thus, the analysis continues at levels 1, 2 and higher. As a result, changes in the signal in different frequency ranges are reflected in separate coefficients. This property is very convenient for detecting impulse, jump and modulated processes.

The mathematical expression of DTT is given by filtered and reduced sequences. The main idea is that the low-frequency part of the signal is re-analyzed in subsequent stages, while the detailed part is preserved. This approach is called "multi-resolution analysis". The selected filter coefficients of the system determine the type of wavelet. Therefore, the selection of a wavelet is essentially equivalent to the selection of a filter bank. In practice, the length and symmetry of the filter significantly affect the quality of the reconstruction. DTT reconstruction is also performed using suitable synthesis filters, and in theory the condition of perfect reconstruction can be met. Therefore, the choice of wavelet should be suitable not only for analysis, but also for signal reconstruction.

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The concept of a delta (impulse) represents a very short-duration, large-amplitude event in a signal. In discrete form, a delta is usually characterized by a value of 1 at one point and a value of 0 elsewhere. Such impulses can appear as a shock in a vibration signal, a contact break in an electrical signal, or a "click" in an audio signal. In DTT, impulses often appear strongly in high-frequency detail coefficients. Therefore, working with details and checking them with threshold or statistical criteria is an effective approach to pulse detection. However, the spread of the impulse depends on the length of the wavelet support, and an incorrect choice can "spread out" the impulse. Therefore, short-base wavelets are often preferred for events close to delta. In addition, the impulse shape may not be an ideal delta, but may be spread out due to system dynamics.

The decomposition level strongly influences the denoising result, as it determines which frequency bands are processed. If chosen too small, low-frequency noise or trend artifacts may be left behind. If chosen too large, the useful slow components of the signal may also be distorted due to excessive smoothing. Therefore, a range is usually chosen, but this depends on the signal length and sampling frequency. If "impulse preservation" is a specific requirement in denoising, the threshold should not be too soft and the wavelet support should not be too long. Otherwise, the impulse may disappear as a diagnostic feature. Also, shift-invariant (e.g., undecimated) methods may be more stable in determining the location of the impulse, but the computational complexity increases. In practical systems, the optimal option is often chosen based on an accuracy-speed trade-off.$JJJ3-7$

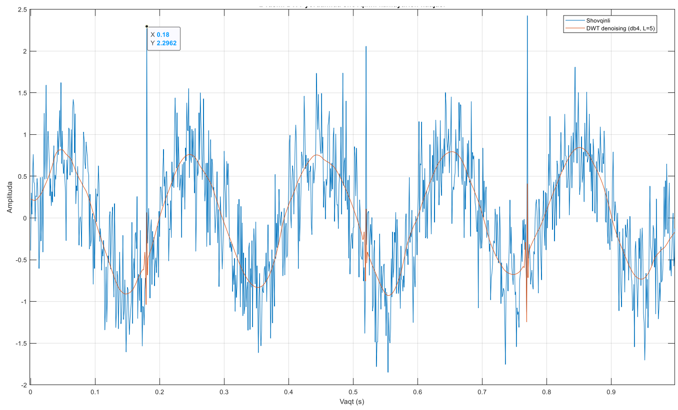

Figure 1. DWT denoising (db4, L=5)

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Hard limit value:

$$\hat{d} = d \cdot \mathbf{1}(|d| \geq T)$$

Soft threshold value:

$$\hat{d} = \text{sign}(d)\max(|d| - T, 0)$$

General (universal) limit value:

$$T = \sigma\sqrt{2\ln\ N}$$

Robust estimation of noise variance:

$$\sigma \approx \frac{\text{median}(|d_1|)}{0.6745}$$

3. Scientific criteria for wavelet selection

The first important criterion for choosing a wavelet is localization in time, that is, the ability to clearly indicate where an event occurred. Localization is mainly determined by the length of the wavelet support. If the support is short, the impulse or sharp jump appears "compressed" in the detailed coefficients and is easier to detect. If the support is long, the same energy is spread over more coefficients and the peak values are reduced. In practical diagnostics, it is precisely the separation of peaks that is very important. Therefore, wavelets such as Haar (db1), db2–db6 or sym2–sym6 are often used for impulse signals. Along with localization, noise sensitivity may also increase, so a balance is maintained with the following criteria. Therefore, the choice of localization is always a compromise depending on the goal.

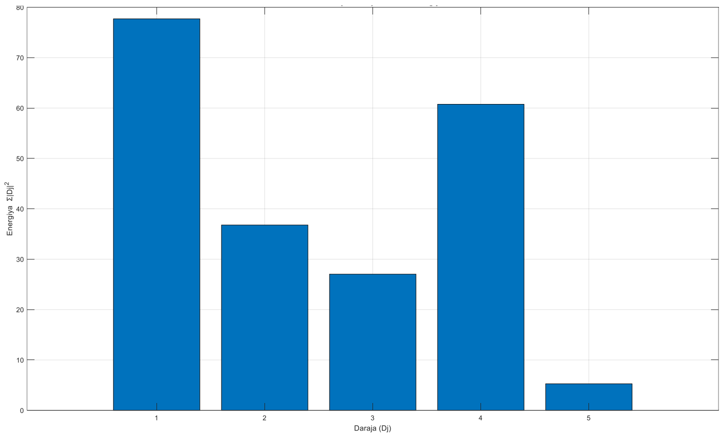

Image code 2: Detail energy by levels

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The second criterion is smoothness and the number of vanishing moments. If there are many vanishing moments, the wavelet polynomial will not reproduce the trends in detail, and the slowly changing parts of the signal will remain in the approximation. This is useful for denoising and feature extraction, because the trend will not be mixed with noise. However, increasing the number of vanishing moments also increases the filter length, which increases the risk of spreading pulses. Therefore, choosing a wavelet with very large moments for impulse events is not always beneficial. For smooth signals (for example, the general contour of an ECG), db8–db12 or coiflets are more suitable. For mixed signals (trend + pulse), wavelets with average moments can be effective. As a result, the number of moments is chosen depending on the trend level of the signal and the detection requirements.

The third criterion is the issue of symmetry and phase distortion, since the preservation of the real signal shape is critical in many tasks. In orthogonal Daubechies wavelets, due to the incomplete symmetry, phase shifts or "skewness" of the shape are sometimes observed. Symlets, and especially biorthogonal wavelets, are almost symmetrical and preserve the shape better during reconstruction. This is very important in medical signals or in the evaluation of sensitive diagnostic features (for example, transient process edges). In addition, biorthogonal wavelets are also widely used in compression and image quality preservation tasks. Orthogonality is necessary for energy conservation and mathematical convenience of coefficients. Thus, there is also a certain balance between "symmetry–orthogonality" in the choice. In practice, the bior/rbio and sym families often serve as universal solutions.

4. Optimal selection according to purpose: a practical guide

4.1. Noise reduction

The main goal of denoising is to reduce the amplitude of the noise while preserving the useful signal components. Since noise is often stronger in the high-frequency range, working with detailed coefficients gives effective results. DTT gives the advantage of "multi-scale" separation of noise from the signal, since noise looks different at different levels. Here, the choice of wavelet depends more on the criteria of smoothness and symmetry. In practice, sym4–sym8, db6–db10

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or coif2–coif5 often give good results. If maximum preservation of the signal shape is required, the bior and rbio families are preferable.

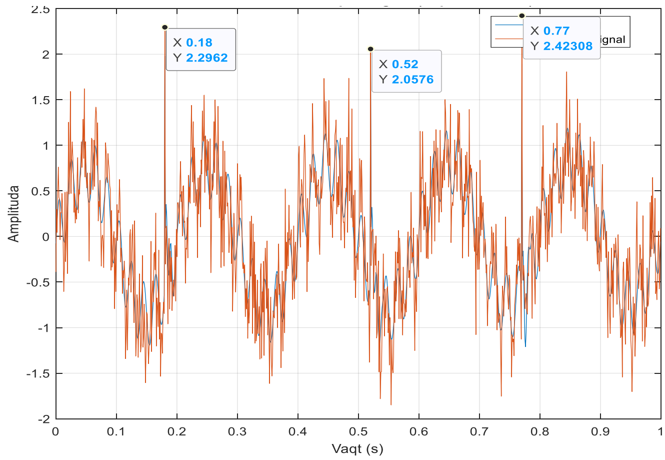

Figure 3. Clean and noisy signal (with pulses)

In denoising, even if the filter length is slightly larger, the threshold must be chosen carefully so as not to "lose" the pulses. Therefore, the wavelet selection is considered together with the threshold policy. The threshold selection is one of the most important steps in denoising, since it is at this stage that the noise is suppressed. Hard threshold sharply reduces the noise coefficients to zero, but can sometimes cause "jumping" artifacts. Soft threshold gives a smooth result, but may also reduce the useful pulse amplitude. Universal threshold works simply and quickly, but may not be the most optimal for all signal types.

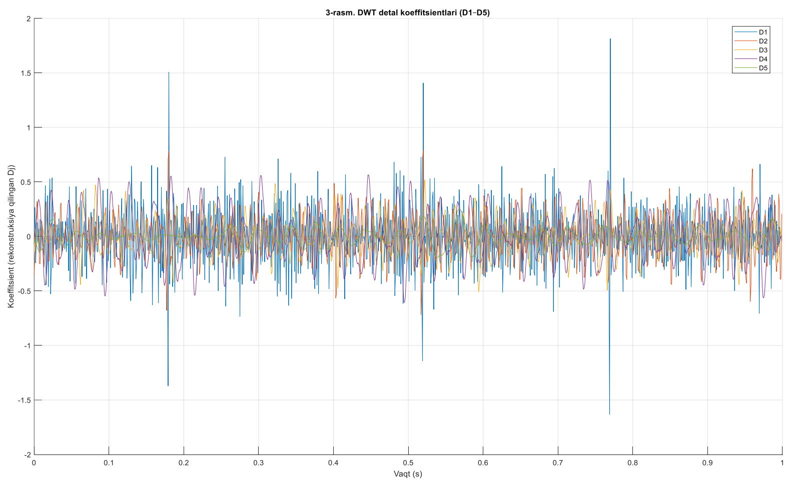

Figure 4. DWT detail coefficients (D1–D5)

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A robust median-based estimate is often used to estimate the noise variance σ. A level-dependent threshold usually gives better results. In addition, the boundary treatment is also important: symmetric filling gives less distortion at the edges. Evaluating the result with metrics such as SNR or MSE helps to refine the denoising parameters.

4.2. Compression

The goal of compression is to represent the signal with as little information as possible and to minimize the error in the reconstruction. DTT is very convenient here, because in most signals the energy is concentrated in a small number of coefficients. The choice of wavelet depends on the energy compaction property, that is, the largest coefficients should give the main content of the signal. For smooth signals, high-momentum wavelets such as db8-db12 can effectively concentrate the energy. When shape preservation and symmetry are important, biorthogonal wavelets also give very good results. In compression, it is possible to work together with stages such as thresholding, quantization and entropy coding of coefficients. However, in the framework of the article, the main attention will be paid to the strategy of wavelet selection and coefficient pruning. As a result, the right choice will increase the compression ratio and preserve the quality of the reconstruction.

In compression, the level of decomposition determines how deeply the low-frequency components of the signal are separated. In most cases, energy is concentrated at low scales, so it is important to choose a sufficient value. In the next step, it is possible to keep the largest coefficient or select a set of coefficients that provide a certain fraction of the energy. If the energy fraction is large, the compression will be effective and the error will remain small. However, too aggressive compression can lose fine details of the signal, which will have a negative effect on diagnostic tasks. Therefore, it should be determined in advance whether the compression goal is "archiving" or "analysis". In image or acoustic signals, psychoacoustic/psychovisual properties can also play a role, but in general signal compression, the energy criterion remains the main one. In practice, several wavelets are tested and the one that gives the smallest error is selected.$JJK\eta$

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The strategy of pruning coefficients from "near-zero" values is also important in the compression process. If the wavelet selection is incorrect, the useful energy will be scattered over many coefficients, and pruning will severely distort the signal. Therefore, the fit of the wavelet to the signal directly determines the quality of the compression. Since biorthogonal wavelets have good symmetry, artifacts are less observed when reconstructing some signals. Although Daubechies wavelets have strong energy compaction, phase distortion can be a problem for some signals. It is also recommended to evaluate the reconstructed signal after compression by MSE, SNR, or correlation. Along with the energy criterion, the preservation of spectral features is also checked, if necessary. Ultimately, the "best" compression is the one that achieves the maximum compression coefficient with the minimum error.

Energy compaction indicator:

$$\eta = \frac{\sum_{i\in\Omega} |c_i|^2}{\sum_i |c_i|^2}$$

4.3. Feature extraction and classification

In the feature extraction task, the DTT coefficients provide "signatures" of the signal at different scales. In diagnostics, for example, bearing failure, uneven loading or resonance phenomena in engine vibrations produce different energy distributions at different levels. Therefore, it is common in practice to extract statistical features such as energy, RMS, kurtosis from the detailed coefficients. In this task, "separability" is important when choosing a wavelet, i.e. the difference between different classes should be clearly visible in the coefficients. For impulsive faults, db2-db6 or sym4-sym6 often separate well. For smooth biological signals, the coif or sym families may be more suitable. In the selection, the power of class separation prevails over preserving the shape of the signal. Therefore, the choice of a wavelet is often confirmed by the results of classification.

For classification, features can be decomposed into levels and collected as separate vectors at each level. For example, the energy at each level can vary significantly when the diagnostic state changes. In addition, entropy features

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represent the level of disorder in the signal and are useful in noisy failures. There is also the problem of overfitting in feature selection, since too many features complicate the model. Therefore, PCA or selection methods extract the most informative features. Wavelet selection can enhance or weaken this informativeness. For example, symmetric wavelets increase the stability of features in some cases. The level of decomposition is also important to find the range in which class differences are visible. Ultimately, the "optimal wavelet" is the wavelet that gives the highest accuracy (Accuracy/F1).$d_j E_j$

In the practical selection process, wavelet $\times J$combinations are tested through cross-validation. In each combination, features are extracted and a classifier (e.g. SVM, Random Forest or neural network) is trained. Then, the best combination is selected based on the validation results. This approach is a "goal-oriented" selection, which validates theoretical criteria with practical metrics. However, a wavelet that is optimal in only one dataset may deteriorate in another, so generalization is checked. Also, changes in noise level, sensor location or loading can affect the result. Therefore, the selection process must cover signals from different modes. The result is a stable and reliable set of wavelet parameters.

Level energy:

$$E_j = \sum_k \left|d_j[k]\right|^2$$

Shannon entropy:

$$H_j = -\sum_k p_k \ln p_k$$

Energy probability:

$$p_k = \frac{\left|d_j[k]\right|^2}{\sum_k \left|d_j[k]\right|^2}$$

4.4. Detection of delta (impulse) events

Detection of impulse events close to delta is one of the most important tasks in many technical systems. Because impulses are often a sign of a fault such as a mechanical shock, a knock in a gear, a crack in a bearing, a “clatter” of electrical

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contacts, or a sensor break. DTT helps to separate the impulse from the noise by showing it at several scales simultaneously. The main focus here is on the detail coefficients, since the high-frequency content of the impulse is strong. When choosing a wavelet, wavelets with a short base and strong localization often give the best results. Haar (db1) is suitable for very sharp impulses, while db2–db4 may be preferable in cases where the impulse is slightly spread out. Sym4–sym6 in some cases retain the impulse shape well and reduce phase distortion. Thus, in impulse detection, the wavelet selection should match the "event shape". Edge processing is also important, because if the impulse is at the beginning or end of the signal, artifacts will be created if the padding is chosen incorrectly. Also, the shift-invariant transformation reduces the sensitivity problem to pulse location. Finally, the detection criteria are optimized based on the Precision–Recall tradeoff.

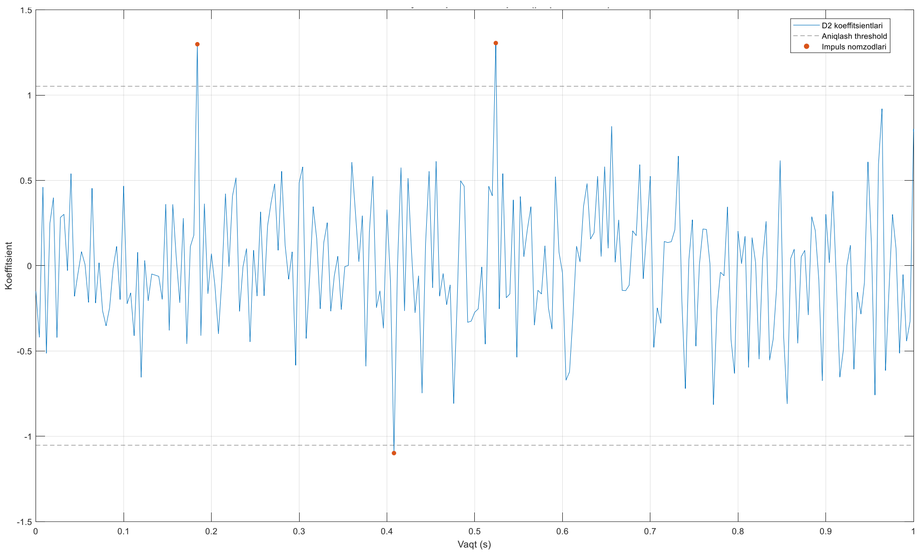

Figure 5: Detection of impulses at D2 level (|D2| > threshold)

Calling the pulse "delta" is an idealization, and in real systems the pulse shape is spread out by a transient process. For example, after a mechanical shock, the system begins to resonate, and the pulse forms a "tail". Therefore, it is sometimes useful to choose a wavelet like matched filtering: if the wavelet shape is close to the shape of the event, the coefficients are maximized. In practice, this is done by testing several wavelets and comparing the quality of their detection with metrics.

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Often, wavelets such as db2, db4, sym4, haar and bior3.5 are tested on pulsed signals. The decomposition level JJJ is selected depending on the pulse duration and sampling frequency, since this determines the range in which the pulse "appears". As a result, along with the separation of the pulse, its location and strength can also be estimated. This approach serves as the basis for early warning systems in technical diagnostics.

5. General algorithm for optimal selection

To put optimal selection into practice, the goal of working with the signal must first be clearly defined. Because denoising, compression, pulse detection or classification tasks do not impose the same requirements on the same parameters. Then the nature of the signal is assessed: it can be pulsed, smooth, trended or mixed. At this stage, a preliminary conclusion is drawn using simple statistics, spectral observations or time graphs. After that, a list of candidate wavelets is compiled and each is selected according to its suitability for the purpose. The selection is based not on the principle of "one wavelet for all", but on the principle of adaptation to the task and signal type. In the next step, the range of parameters is determined, for example, JJJ levels, threshold types and boundary methods. Then the metric is selected, since measuring optimality is impossible without a criterion. The grid-search or cross-wave approach is one of the most reliable methods for working with candidates. In this case, the results are calculated systematically for each wavelet type and parameter combination. For each combination, the SNR or MSE in denoising, the reconstruction error and compression coefficient in compression, and the F1 or ROC indicators in detection are evaluated. The results are compared in a table and the best combination is selected. However, relying on a single test result can be misleading, so verification on several signal samples is required. This verification should cover different modes, different noise levels, and different sensor locations. Only then will the selected wavelet parameters be generalizable and stable. Finally, the computational complexity of implementation in a practical system is also taken into account.

Once the selection is complete, it is also advisable to check the physical meaning of the result. For example, in vibration diagnostics, the pulses detected should

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really correspond to a mechanical event. Otherwise, the algorithm may perceive noise as a "fault". It is also useful to compare with biorthogonal wavelets if the shape and phase of the reconstructed signal are important. If the parameters are too sensitive, that is, a small change drastically changes the result, this indicates a stability problem. In this case, it is possible to consider the option of making the threshold adaptive or shift-invariant transformation. Another important point is that in real-time systems, computational resources are limited, so wavelets with very long filters are not always suitable. Thus, the optimal choice always requires a balance between accuracy, stability and computational speed. As a result, the final configuration is obtained that meets the system requirements.

Discussion

One of the most common mistakes in practice is to choose the decomposition level as "more is better". In fact, too large a JJJ selection can oversmooth low-frequency useful components or amplify boundary artifacts. The second mistake is to choose the wrong threshold, for example, to assume that the universal threshold is optimal in all cases. The universal threshold may also suppress useful components in some signals. The third problem is to ignore the padding method, because artifacts formed in the boundary regions will cause false signals in pulse detection. The fourth mistake is to constantly use the wavelet type without testing, because when the signal type changes, the optimal wavelet also changes. The fifth point is to evaluate the result without metrics, that is, to draw conclusions only by eye. The most correct approach is to use theoretical criteria together with practical metrics. As recommendations, first of all, it is necessary to clearly define the signal target and choose an evaluation metric. Criteria such as SNR and MSE in denoising, F1 and false alarm rate in pulse detection, and reconstruction error in compression should be under constant control. The second recommendation is to test several wavelet families and systematically compare them. The third is to make the threshold adaptive by level, since the noise may not appear the same at all levels. The fourth is to choose a symmetric thresholding and check separately if the pulse is on the edge. The fifth is to limit the filter length in order to reduce the computational complexity for real-time systems. The sixth is to check the stability of the parameters, that is, to see if the result does not deteriorate under

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different samples and conditions. These recommendations significantly increase the likelihood of optimal use of DTT. Another important aspect of the discussion is the issue of correctly distinguishing between pulse and noise. Some types of noise can also appear in the form of pulse-like "spike", which complicates detection. In this case, multi-scale validation and additional statistical filtering help. Also, when the pulses are periodic, such as in the case of a bearing failure, the pulse interval also becomes a diagnostic feature. It is possible to extract the pulse sequence from the DTT coefficients and then add time interval analysis. This approach allows not only to determine "present/absent", but also to classify the type of fault. However, in such a complex system, the wavelet selection becomes more responsible, since the wrong choice also violates the subsequent analysis stages. Therefore, it is correct to consider the wavelet selection as the "main filter stage" of the diagnostic chain. As a result, the advantages of DTT are fully manifested.

Conclusion

Discrete wavelet transform provides powerful theoretical and practical capabilities for targeted processing of received signals. Its main advantage is the ability to detect local phenomena in time in non-stationary signals at different scales. However, the real efficiency of DTT directly depends on the correct choice of wavelet type and parameters. For events close to the impulse (delta), wavelets with short bases and strong localization often give the best results. In denoising and compression, smoothness, energy compaction, and symmetry criteria are more important. In feature extraction and classification, the optimal choice must be confirmed by metrics. Therefore, the wavelet selection process should be based on a systematic approach that combines trial and error and theoretical analysis. As a result, using DTT, signal quality, detection reliability, and diagnostic accuracy are significantly increased.

The methodological approaches presented in the article suggest forming a list of wavelets suitable for the signal type and optimizing them together with the parameters. This approach is considered to be more stable and effective in practical systems than "random selection". It was also noted that parameters such as threshold and boundary processing are no less important than wavelet

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selection. In pulse detection, it is very important to balance false signals and omission errors, for which adaptive threshold and multi-scale verification are effective. In compression, the energy fraction and reconstruction error are the main criteria, and the degree to which the wavelet can accumulate energy plays a decisive role. In classification, the best wavelet is the one that gives the highest F1 or accuracy. In conclusion, it was shown that the optimal selection is always a compromise between accuracy, stability and calculation speed. On this basis, practical recommendations were formulated for the reliable implementation of DTT in various areas.

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