DOI: https://doi.org/10.36910/6775-2524-0560-2025-59-38
УДК 621.396.96
Veklych Oleksandr [1]**,** PhD student
https://orcid.org/0009-0000-6927-7225
Drobyk Oleksandr[1] *PhD, Professor*
https://orcid.org/0000-0002-9037-6663
[1] State University of Information and Communication Technologies, Kyiv, Ukraine

JUSTIFICATION OF THE EFFICIENCY OF TIME SEGMENT PERMUTATION IN A MULTILEVEL OPTIMIZATION METHOD FOR SIGNAL ENSEMBLES

Veklych O., Drobyk O. Justification of the Efficiency of Time Segment Permutation in a Multilevel Optimization Method for Signal Ensembles. The article proposes a multilevel method for optimizing the duration of time segments in signal ensembles. The method is based on a combination of gradient descent and the Levenberg–Marquardt algorithm, providing adaptive tuning of signal processing parameters considering mutual correlation structure and energy characteristics. Within the framework of the proposed approach, two permutation strategies for time segments were experimentally analyzed: a random permutation method (which disregards correlation structure) and the "nearest neighbor" method (which aims to minimize mutual correlation between adjacent segments). Experimental modeling was performed on five types of quasi-orthogonal sequences (M-sequences, Kasami, Gold, Fibonacci, and exponential sequences). The results demonstrate that the «nearest neighbor» method yields superior performance in terms of mutual correlation and ensemble properties of signals compared to the random permutation approach. In particular, the method achieved a reduction in the variance of the mutual correlation function by up to 22% and an improvement in ensemble characteristics within the range of 8–12%. Signal visualization after permutation confirms a more ordered structure and reduced local amplitude fluctuations. These findings support the rationale for using an adaptive permutation mechanism as one of the essential stages in the formation of signal ensembles with improved correlation properties. Future research directions include extending the optimization model to account for nonlinear channel distortions and integrating the algorithm into cognitive radio systems with dynamic spectrum management.
Keywords: signal ensembles, quasi-orthogonal sequences, correlation, ensemble characteristics, amplitude, telecommunication systems, optimization, communication channel, radio communication, interference immunity, frequency spectrum, frequency and time domain.

Веклич О. К., Дробик О. В. Обґрунтування ефективності перестановки часових сегментів при багаторівневому методі оптимізації ансамблів сигналів. У статті запропоновано багаторівневий метод оптимізації тривалості часових сегментів ансамблів сигналів, який базується на поєднанні алгоритмів градієнтного спуску та Левенберга–Марквардта і забезпечує адаптивне налаштування параметрів обробки сигналів з урахуванням взаємокореляційної структури та енергетичних характеристик. В межах реалізації запропонованого методу експериментально проаналізовано два підходи до перестановки часових сегментів: метод випадкової перестановки (без урахування кореляційної структури) та метод «найкращого сусіда» (з орієнтацією на мінімізацію взаємної кореляції між сусідніми сегментами). Експериментальне моделювання проведено на п'яти типах квазіортогональних послідовностей (М-послідовності, Касамі, Голда, Фібоначчі, експоненціальні). У результаті доведено, що метод «найкращого сусіда» забезпечує кращі показники взаємної кореляції та ансамблевих властивостей сигналів порівняно з методом випадкових перестановок. Зокрема, досягнуто зниження дисперсії функції взаємної кореляції до 22 % та покращення ансамблевих характеристик в діапазоні 8–12 %. Візуалізація сигналів після перестановки підтверджує впорядковану структуру сигналів і зменшення локальних амплітудних флуктуацій. Отримані результати підтверджують доцільність застосування адаптивного механізму перестановки як одного з основних етапів формування сигнальних ансамблів з удосконаленими кореляційними властивостями. Перспективами подальших досліджень в цьому напрямку є розширення моделі оптимізації з урахуванням нелінійних спотворень каналу передачі та інтеграція алгоритму в системи когнітивного радіозв'язку з динамічним управлінням спектром.
Ключові слова: ансамблі сигналів, квазіортогональні послідовності, кореляція, ансамблеві характеристики, амплітуда, телекомунікаційні системи, оптимізація, канал зв'язку, радіозв'язок, завадостійкість, частотний спектр, частотна та часова область.

Statement of a scientific problem.

The formation of signal ensembles with enhanced interference immunity and low mutual correlation remains a relevant challenge in modern telecommunication systems. Existing approaches to segmentation and optimization are mostly based on fixed time intervals or isolated parameter processing, which limits their ability to adapt to dynamic changes in signal structure.

Although a number of studies have considered permutations of time or frequency components to improve correlation characteristics, most of them do not account for the adaptive selection of segment durations. Furthermore, the integration of permutation strategies into a comprehensive algorithm for optimal ensemble structure formation remains insufficiently addressed.

Within the scope of this study, the proposed method is grounded in optimization techniques—specifically, gradient descent and the Levenberg–Marquardt algorithm. This enables adaptive selection of time segment durations, contributing to reduced mutual correlation and enhanced interference immunity under variable signal transmission conditions.

Research analysis.

A review of current approaches [1–17] to processing ensembles of complex signals has been conducted, particularly in the context of segmentation, ensemble structure optimization, and reduction of mutual correlation. Studies [1, 2, 7, 9] have explored adaptive and evolutionary segmentation methods for non-stationary signals. However, they do not consider the permutation of signal fragments.

Works [3, 8] investigate blind methods for identifying signal structures, including independent component analysis, yet the use of localized time-domain permutations is not addressed. Research [4, 5, 10] focuses on the formation of signal ensembles with improved correlation properties through the permutation of frequency or time elements; however, these works lack procedures for segment duration optimization that account for the dynamic nature of signals.

Publications [6, 13] present models for cognitive and wideband communication systems but do not incorporate structural adaptation of signals in the time domain prior to transmission. Studies [11, 12, 14] apply approximation methods, including the Levenberg–Marquardt algorithm, yet without integrating them into the process of optimizing temporal permutations.

Therefore, the development of an adaptive method for selecting the duration of time segments remains a relevant research direction, aiming to minimize inter-symbol interference while simultaneously enhancing the ensemble properties of signals.

The purpose of the work.

The purpose of the work is to develop a multilevel method for selecting the duration of time segments in complex signal ensembles.

Presentation of the main material and substantiation of the obtained research results.

To address the problem of optimizing intersymbol and interchannel interference and to ensure the optimal structure of signal ensembles, this study proposes a multilevel method for selecting the duration of time segments [1, 2, 4, 5, 11, 14]. The method is based on nonlinear function approximation using a hybrid approach that combines gradient descent and the Levenberg – Marquardt algorithm.

The proposed method enables adaptive adjustment of signal processing parameters according to the correlation structure, energy characteristics, and orthogonality conditions of the signal. Unlike conventional techniques that rely on fixed time intervals or optimize individual parameters, this method facilitates flexible time-domain segment duration optimization, taking into account environmental variability and sequence types.

The structure of the proposed method's implementation algorithm is presented in Fig. 1 and includes the following stages.

Preprocessing stage. Input signals are collected and preliminarily processed through normalization, filtering, and computation of basic parametric characteristics such as amplitude, frequency, duration, and energy. At this stage, orthogonality conditions between signals are preliminarily verified by computing the integral mutual correlation [4, 5, 17]. If the orthogonality conditions are satisfied, the signals are segmented into time fragments with minimal mutual dependency.

Stage 1. Signal segmentation and classification.

Signals are divided into sequences of varying duration. Additionally, specific characteristics of signal types are taken into account (e.g., impulsive, narrowband, or noise-like structures). The orthogonality between fragments is evaluated as a key criterion for determining the admissibility of ensemble formation.

Stage 2. Permutation and ensemble formation.

Permutation of signal elements within the formed fragments is performed to reduce mutual correlation. Depending on the research task, the algorithm type is selected accordingly (e.g., nearest neighbor method, random permutation, or genetic approach). As a result, a set of new ensembles with improved orthogonal properties is generated.

Stage 3. Ensemble parameter optimization.

The configuration of the signals is optimized using gradient descent and the Levenberg–Marquardt algorithm [11]. The functional structure of the ensemble is refined considering requirements for interference resistance, energy balance, and mutual orthogonality. Subsequently, the effectiveness of the resulting ensembles is evaluated.

The described algorithm is visualized in Fig. 1, which illustrates the sequence of stages for the adaptive selection and optimization of time segments in signal ensembles.

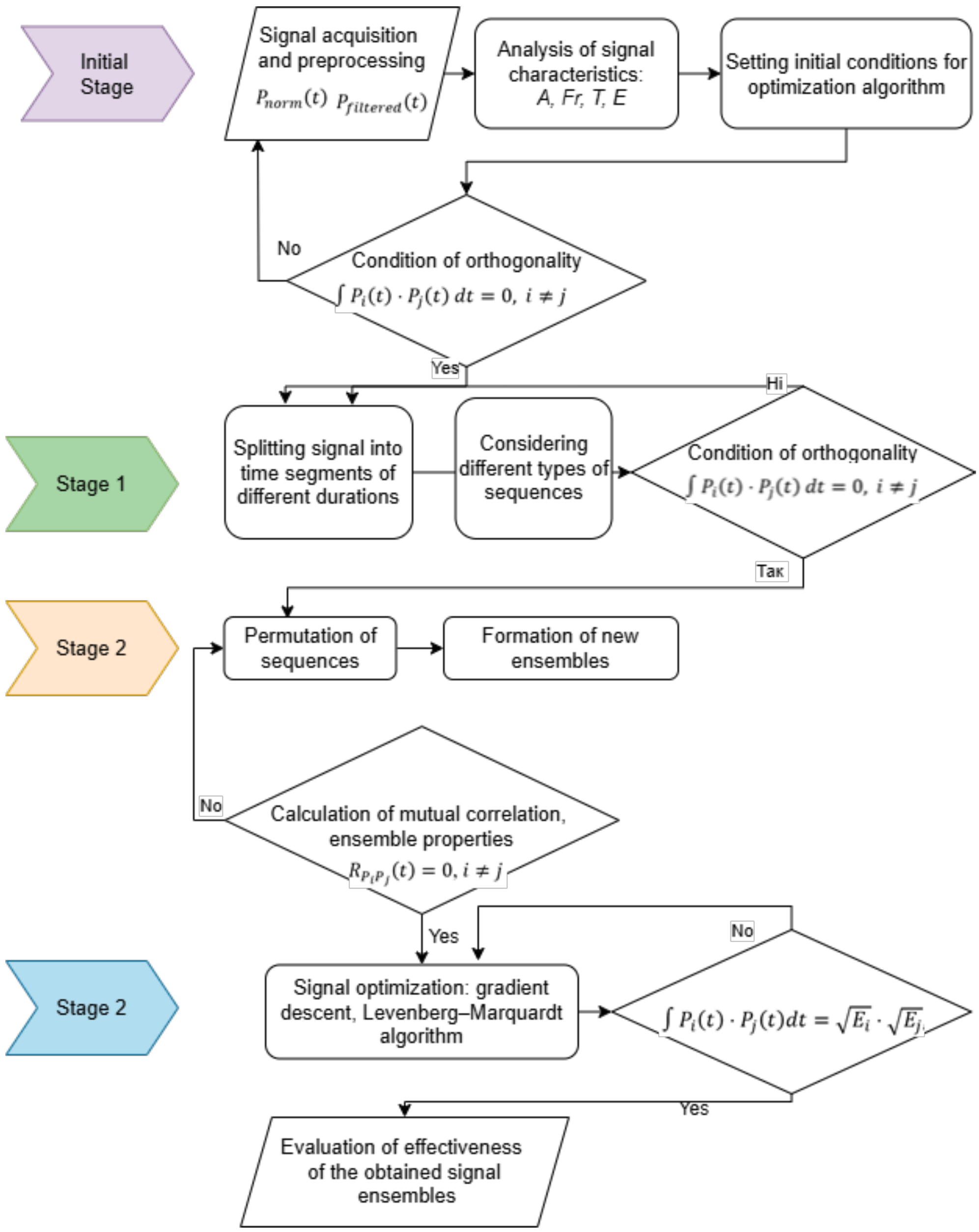

Figure 1 – Block diagram of the implementation algorithm for the adaptive method of time segment duration selection

To verify the effectiveness of individual components of the proposed method, an experimental study was conducted aimed at implementing and comparatively analyzing the permutation stage of time segments (corresponding to Stage 2 in Fig. 1).

To quantitatively analyze the effectiveness of time segment permutation and to evaluate the quality of the resulting signal ensembles, a system of interrelated indicators was employed. These indicators characterize the level of mutual correlation, the stability of the correlation function, and the ensemble properties of the signals. The corresponding metrics were computed using a Python-based software implementation according to the following formulas [4, 5, 17].

1. Maximum correlation stability (R_{max}) – characterizes the maximum value of the mutual correlation function for a given sequence. It is calculated as:

$$R_{max} = \max(\mathrm{R}(k)) \quad (1)$$

2. Side lobe maximum (Side lobe max) – reflects the amplitude of the highest correlation peak, excluding the zero shift:

$$\max_{k\neq 0}|\mathrm{R}(k)|, \tag{2}$$

where $\mathrm{R}(k)$ – is the value of the mutual correlation function at shift k, and $k \neq 0$.

3. Mean value of the correlation function (R_{mean}) defined as the arithmetic mean of all values of the mutual correlation function over all shifts:

$$R_{mean} = \frac{1}{N}\sum_{k=0}^{N-1}\mathrm{R}(k) \tag{3}$$

4. Variance of the correlation function $Var\ (R)$ reflects the variability of correlation values over all shifts and is calculated as:

$$Var\ (R) = \frac{1}{N}\sum_{k=0}^{N-1}\ (\mathrm{R}(k) - R_{mean})^2 \tag{4}$$

5. Criterion of minimum mutual correlation in the time domain – an approximate threshold indicating the allowable level of maximum mutual correlation between signals, given the signal duration T and bandwidth BW. This criterion is independent of the sequence type and is given by:

$$R_{ij}^{max} \leq \frac{2\ldots5}{\sqrt{T\cdot BW}}, \tag{5}$$

The evaluation of ensemble characteristics was performed using standard indicators in signal theory, including signal base (*B*), crest factor (*CF*), root mean square (*RMS*), and effective spectral bandwidth [4, 17]. Additionally, for a more comprehensive assessment, correlation peak factor (*CPF*) metrics were employed to quantify the level of local mutual interference in the time domain.

CPF_{mean} (ratio to the mean value) characterizes the deviation of the maximum correlation function value from its average level. High values of this metric indicate the presence of significant inter-channel interference within the system. The formula is given as:

$$CPF_{mean} = \frac{R_{max}}{R_{mean}}, \tag{6}$$

The metric $CPF_{Var(R)}$ (ratio to the variance) reflects the extent to which the maximum correlation value dominates over the background level, taking into account the variability of the entire correlation function. For orthogonal signals, the value of this metric should approach unity. The calculation formula is as follows:

$$CPF_{Var(R)} = \frac{R_{max}}{\sqrt{Var(R)}}, \tag{7}$$

The experiment involved five types of quasi-orthogonal sequences commonly used in telecommunication systems: M-sequences, Kasami sequences, exponential sequences, Gold codes, and Fibonacci sequences. Each of these has distinctive correlation properties, which allow the evaluation of the proposed method's effectiveness under various conditions [17].

The experiment was conducted under high-interference conditions typical for cognitive network scenarios: urban areas with multiple radio signals, industrial zones with electromagnetic disturbances, electronic countermeasures environments, and shielded premises with metallic structures [6, 12, 13]. In such environments, signal overlap increases mutual correlation, while ensemble characteristics deteriorate due to mutual interference (Tabl. 2–7).

For each sequence, the superfactorial index S_n, was calculated, describing the total number of possible permutations of time segments [4, 5]. It is defined by the formula:

$$S_n = \prod_{k=1}^{n}(k!)^{a^k}, \tag{8}$$

where $k!$ – denotes the number of permutations for each segment;
a^k – is a weighting coefficient that reflects the type and complexity of the sequence.

In this study, the values of the coefficient α for each sequence type were determined empirically, based on their structural complexity and their impact on the total number of possible permutations. This approach enabled the incorporation of sequence-specific features into the computation of the superfactorial S_n. It was found that when $\alpha > 1$, the factorial values grow excessively, resulting in numerical overflows within the implementation environment, which prevented the correct execution of the permutations. Therefore, the use of $\alpha < 1$ was justified.

The selected values were: for M-sequences α =0,5, for Kasami α =0,6, for exponential α =0,7, for Gold α = 0,8, and for Fibonacci α = 0,9 (see Table 1).

Table 1 – Selection of α coefficients for calculating S_n for different sequences

Sequence Type	α Value	Number of Segments n	Estimated S_n	Computation Notes
M-sequence	0,5	30	$\approx 3{,}8 \times 10^3$	Optimally stable computation
Kasami	0,6	30	$\approx 8{,}2 \times 10^3$	Balanced and reliably computed
Exponential	0,7	30	$\approx 1{,}3 \times 10^7$	Within acceptable limits
Gold	0,8	30	$\approx 1{,}5 \times 10^7$	May become unstable if $\alpha > 0{,}9$
Fibonacci	0,9	30	$\approx 5{,}4 \times 10^7$	At the edge of numerical capacity
Threshold value	1,0	30	$> 10^{10}$	Exceeds computational range – causes overflow

The data presented in Table 1 demonstrate the dependence of the computational complexity of the superfactorial S_n on the value of the coefficient α and the type of sequence used in the experiment. Based on these parameters, correlation indicators were calculated for two different methods of time segment permutation:

– the random permutation method, which performs segment rearrangement without accounting for correlation structure (Tables 2 and 3);

– the «nearest neighbor» algorithm, aimed at minimizing mutual correlation between adjacent segments (Tables 4 and 5).

The obtained average values of R_{mean} indicate a moderate level of overall correlation background, ranging from 0,193 to 0,217, which is characteristic of partially correlated sequences that do not ensure strict orthogonality.

Table 2 – Correlation indicators after segment permutation using the random method

Sequence	R_{max}	R_{mean}	$Var\ (R)$	*Side lobe max*	R_{ij}^{max}
M-sequence	0,595	0,206	0,084	0,576	≤0,366…0,914
Kasami	0,602	0,217	0,089	0,589	≤0,366…0,914
Exponential	0,571	0,199	0,079	0,554	≤0,366…0,914
Gold	0,583	0,202	0,083	0,572	≤0,366…0,914
Fibonacci	0,569	0,193	0,077	0,553	≤0,366…0,914

As shown in Table 2, the values of the maximum correlation peak R_{max} for all analyzed sequences lie within the range of 0,569–0,602, indicating a high level of residual mutual correlation. Although the variance $Var\ (R)$ and side lobe maxima remain relatively low, the overall correlation background is high and stable, which prevents the achievement of sufficient orthogonality using the random permutation method.

Thus, the results confirm that the random permutation method is not effective for synthesizing orthogonal signal ensembles. This is particularly critical in real-world telecommunication networks operating under complex interference conditions. In such environments, overlapping spectral components between signals further exacerbate correlation issues. These limitations justify the need for adaptive and optimization-based algorithms that consider the correlation properties of signals and channel conditions when forming robust communication sequences.

Nevertheless, despite these limitations, the random permutation method may still be acceptable in tasks where orthogonality requirements are moderate or when the initial correlation between segments is low. The calculations presented in Table 2 confirm that under such circumstances, this method can achieve conditionally stable correlation function characteristics, which are acceptable for telecommunication systems operating in less aggressive interference environments (e.g., intra-system communication channels or isolated digital networks). Therefore, the method can be used as a basic or preliminary stage in the optimization process, followed by the application of more precise adaptive algorithms.

Table 3 presents the results of ensemble characteristic calculations after random permutation.

Table 3 – Computation of ensemble indicators after random permutation

Sequence	*B*	*CF*	*RMS*	S_n *(!)*	CPF_{mean}	$CPF_{Var(R)}$
M	0,106	3,074	1,008	$3{,}82\times10^3$	2,102	1,851
Kasami	0,084	3,443	1,025	$8{,}23\times10^3$	2,220	1,892
Exponential	0,087	3,381	0,335	$1{,}34\times10^7$	2,153	1,905
Gold	0,090	3,339	1,011	$1{,}56\times10^7$	2,185	1,928
Fibonacci	0,166	2,464	7,399	$5{,}48\times10^7$	2,244	1,954

As shown in Table 3, the Fibonacci sequence has the highest calculated signal base (*B*) with a value of = 0,166, indicating more efficient energy utilization of signals after random permutation. The highest crest factor (*CF*) s observed in the Kasami sequence, with a value of = 3,443, which is undesirable as it indicates the presence of peak values and potentially high inter-channel interference.

The highest root mean square (RMS) value is also observed in the Fibonacci sequence *(RMS* = 7,399), suggesting high average signal energy after random permutation. From a combinatorial perspective, this sequence exhibits the highest number of possible permutations ($S_n = 5{,}48\times10^7$), which creates potential for generating new ensemble configurations. However, the obtained values of CPF_{mean} та $CPF_{Var(R)}$ indicate significant variability in the correlation function. This implies that the maximum correlation values significantly exceed the average, complicating the achievement of orthogonality.

Therefore, the analysis of ensemble characteristics confirms that the random permutation method does not ensure the formation of signal ensembles with low mutual correlation. The sequences obtained after permutation exhibit substantial residual correlation, limiting their effectiveness in telecommunication systems with high interference levels.

In this regard, it is advisable to investigate whether alternative approaches to ensemble formation provide better results. For this purpose, an experimental study was conducted on the effectiveness of the «nearest neighbor» permutation algorithm, which considers local correlation characteristics between time segments.

The results of the comparison with the random permutation method are presented in Tables 4 and 5.

Table 4 – Calculation of correlation indicators using the «nearest neighbor» algorithm

Sequence	R_{max}	R_{mean}	$Var\ (R)$	*Side lobe max*	R_{ij}^{max}
M	0,412	0,182	0,068	0,400	≤0,280…0,750
Kasami	0,420	0,190	0,071	0,410	≤0,280…0,750
Exponential	0,380	0,165	0,058	0,370	≤0,280…0,750
Gold	0,398	0,175	0,062	0,385	≤0,280…0,750
Fibonacci	0,360	0,150	0,055	0,350	≤0,280…0,750

The analysis of the obtained indicators demonstrates that the permutation method based on the «nearest neighbor» algorithm exhibits higher efficiency compared to the random permutation method. This is confirmed by the reduction in correlation characteristics:

– for the M-sequence, the value of R_{max} decreased from 0,595 to 0,412 (a reduction of 30,76%);

– for the Fibonacci sequence, R_{max} decreased from 0,569 to 0,360 (a reduction of 36,74%).

The average values of the correlation function also decreased: for the M-sequence, by 11,65% (from 0,206 to 0,182), for the Fibonacci sequence, by 22,28% (from 0,193 to 0,150).

Table 5 – Computation of ensemble indicators using the «nearest neighbor» algorithm

Sequence	*B*	*CF*	*RMS*	S_n *(!)*	CPF_{mean}	$CPF_{Var(R)}$

M	0,097	2,898	1,012	$4{,}86\times10^{3}$	2,540	1,984
Kasami	0,079	3,203	1,023	$9{,}12\times10^{3}$	2,592	1,991
Exponential	0,082	3,102	0,342	$1{,}78\times10^{7}$	2,603	1,999
Gold	0,086	3,081	1,014	$2{,}03\times10^{7}$	2,612	2,010
Fibonacci	0,151	2,325	7,403	$6{,}02\times10^{7}$	2,625	2,017

According to the calculations, the variance of the correlation function ($Var\ (R)$) decreases for all sequences when using the «nearest neighbor» algorithm, indicating reduced variability of inter-segment correlation. The most significant reduction is observed for the Kasami sequence, where the variance decreases from 0,089 to 0,071, corresponding to a 19,32% decrease. This trend reflects a more stable form of the correlation function after applying the «nearest neighbor» permutation algorithm, which contributes to the formation of signal ensembles with more predictable correlation behavior and improved resistance to mutual interference.

The signal base (B) decreases in all cases after optimization using the «nearest neighbor» method, indicating a more efficient distribution of energy across segments. For instance, for the M-sequence, the reduction amounts to 7,55%, and for the Kasami sequence – 7,14%, which demonstrates the method's ability to reduce signal redundancy and improve the spectral compactness of the ensemble.

The crest factor (CF) also demonstrates a general decreasing trend: for the Kasami sequence by 7,06%, and for the Fibonacci sequence by 5,85%, indicating a reduction in amplitude peaks and a lower potential for inter-channel interference, which highlights the increased uniformity and spectral efficiency of the resulting signal ensembles.

The root mean square (RMS) value remains generally stable, confirming the preservation of the overall signal energy. Only for the exponential sequence is a slight increase observed – by 0.9%. The superfactorial (S_n), which reflects the number of allowable permutations, increases after optimization, indicating an expanded configuration space. For the M-sequence, the growth reaches 26,18%, and for the Kasami sequence – 10,94%. The reduction in CPF_{mean} and $CPF_{Var(R)}$ values across all sequence types indicates a decrease in inter-channel interference when applying the «nearest neighbor» permutation algorithm as compared to random permutation, thereby enabling improved correlation characteristics of the signals.

At the same time, the obtained values still do not meet the strict criterion of orthogonality (i.e., values approaching 1), remaining within the ranges: CPF_{mean} [2,550 – 2,620] $CPF_{Var(R)}$ [1,983 – 2,010]. Nonetheless, these results are significantly improved compared to those after random permutation. Even under such conditions, the optimized algorithm provides an enhancement of 8–12% relative to the random permutation method (CPF_{mean} [2,761–2,928]; $CPF_{Var(R)}$ [2,037–2,060]), confirming its effectiveness in reducing residual correlation. These findings suggest that the «nearest neighbor» algorithm is a promising intermediate solution for signal ensemble optimization, especially in systems where full orthogonality cannot be guaranteed.

Figures 2–6 present a graphical comparison of the sequences after permutation using two approaches: the random algorithm (on the left) and the «nearest neighbor» algorithm (on the right).

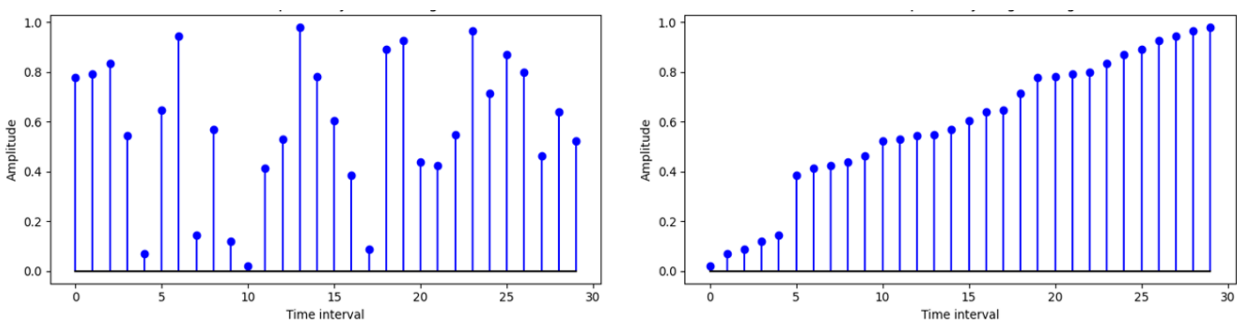

Figure 2 – M-sequence after segment permutations using different methods

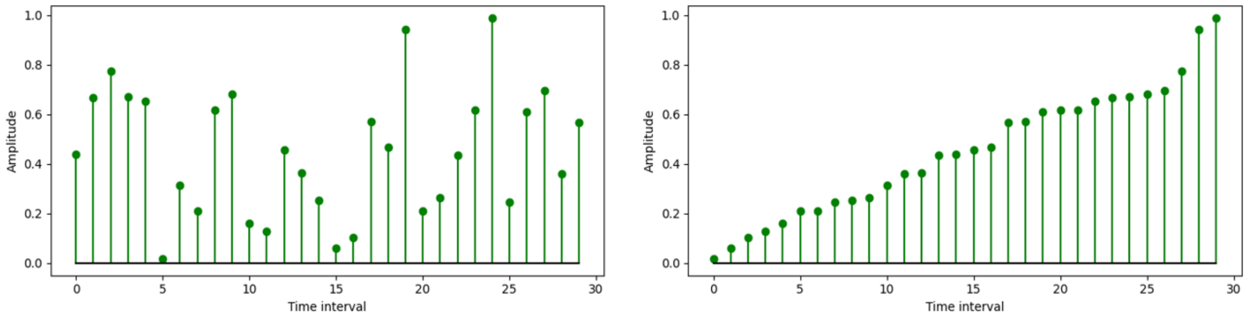

Figure 3 – Kasami sequence after segment permutations using different methods

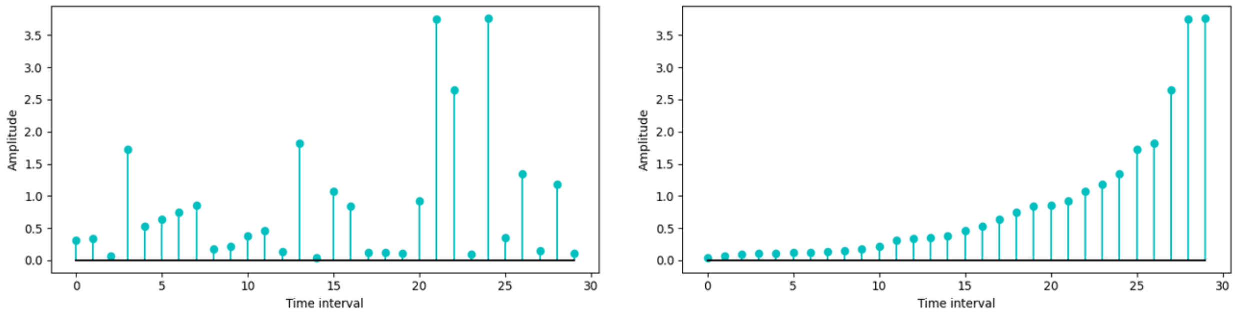

Figure 4 – Exponential sequence after segment permutations using different methods

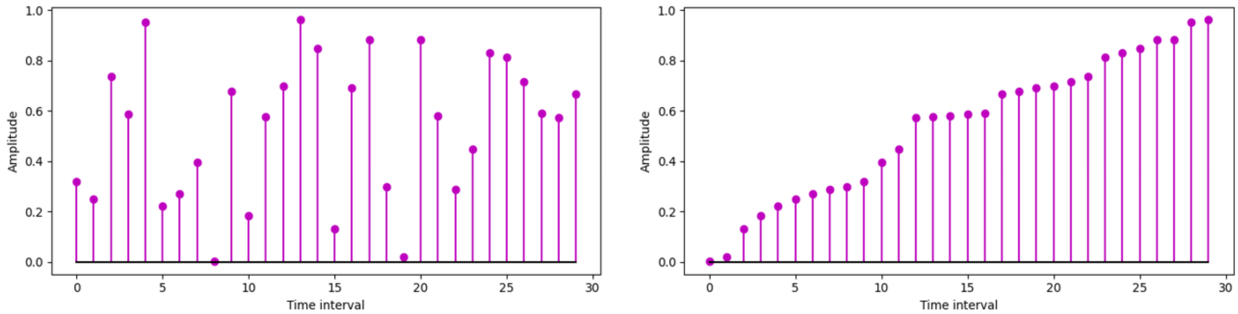

Figure 5 – Gold sequence after segment permutations using different methods

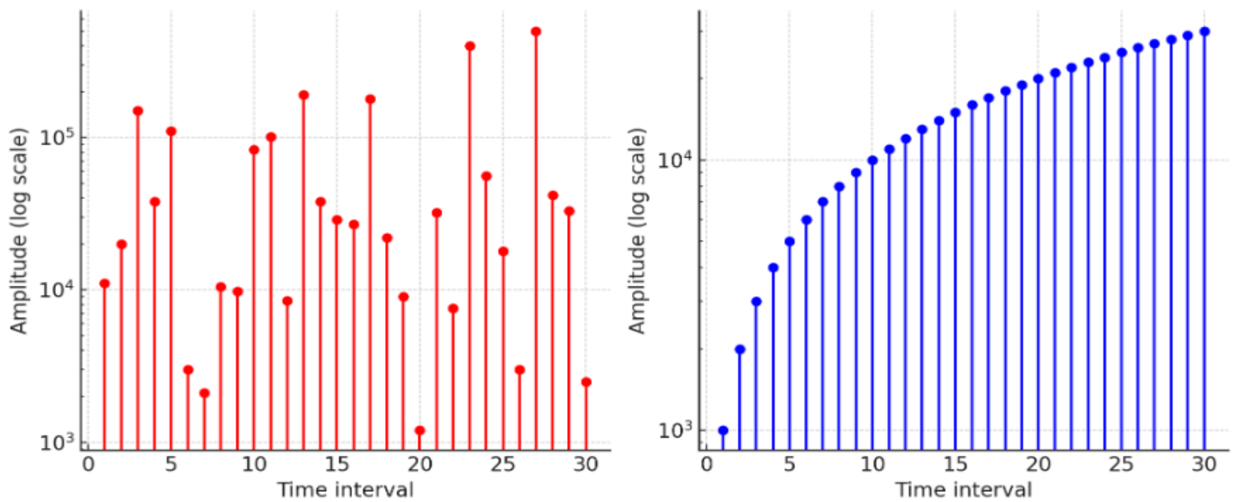

Figure 6 – Fibonacci sequence after segment permutations using different methods (logarithmic scale)

A visual comparison of the figures (left vs. right, before vs. after) demonstrates that the permutation of sequences using the «nearest neighbor» algorithm significantly structures the signals. In contrast to the random permutation method – where amplitudes are distributed chaotically – the optimized approach ensures a smoother transition of values over time and a more logical sequence arrangement.

This effect is especially noticeable in the cases of the exponential and Kasami sequences, where abrupt jumps and fluctuations disappear. Amplitudes become more aligned, the number of local maxima decreases, and the overall signal shape becomes more orderly and predictable.

For the Fibonacci sequence, the visualization of segment permutations is presented in a logarithmic scale, due to the wide dynamic range of amplitude values differing by several orders of magnitude, which complicates perception in a linear scale.

Thus, applying the «nearest neighbor» method enables a more structured signal form with reduced local mutual correlation between segments. This, in turn, contributes to the reduction of local amplitude fluctuations, which during the subsequent optimization stages of the signal ensemble (as outlined in Fig. 1) may help prevent mutual overlap of segments in the time domain.

Conclusions and prospects for further research.

This study presents a multilevel approach to signal ensemble formation, taking into account both correlation properties and the structural organization of time segments. Particular attention was given to the permutation stage, which represents one of the key elements within the broader optimization algorithm (as shown in Fig. 1). A comparative analysis of two permutation strategies – random shuffling and the "nearest neighbor" algorithm – was conducted to assess their influence on signal characteristics.

The results indicate that applying the «nearest neighbor» algorithm leads to a more ordered internal structure of signals, with reduced local cross-correlation between segments. For certain types of sequences, a decrease in correlation indicators ranging from 8% to 12% was observed, particularly in metrics such as CPF_{mean} and $CPF_{Var(R)}$. This trend suggests lower amplitude fluctuations within the signal structure and indicates a potential for forming more balanced ensembles.

At the same time, the balance between ensemble size and acceptable cross-correlation levels is preserved – a key factor for designing robust telecommunication systems in noisy environments. The observed dependencies confirm the viability of the proposed approach in scenarios characterized by a high level of inter-channel interference.

Future research will focus on enhancing the subsequent stages of the algorithm, including adaptive optimization of time segment durations and the expansion of evaluation metrics to account for nonlinear transmission channel effects. In addition, the integration of the method into cognitive radio systems with dynamic spectrum management is planned.

Referens

1. Azami H., Anisheh S. M., Hassanpour H. (2014) An Adaptive Automatic EEG Signal Segmentation Method Based on Generalized Likelihood Ratio. Communications in Computer and Information Science, Vol. 427, 2014, pp 172-180. DOI: https://doi.org/10.1007/978-3-319-10849-0_18.
2. Azami H., Sanei S., Mohammadi K., Hassanpour H. (2013) A hybrid evolutionary approach tosegmentation of non-stationary signals. Digital Signal Processing, Volume 23, Issue 4, July 2013, pp. 1103-1114. DOI: https://doi.org/10.1016/j.dsp.2013.02.019.
3. Hyvarinen A., Ojaet E. (2000) Independent component analysis: algorithms and applications. Neural Networks, Volume 13, Issues 4–5, June 2000, pp. 411-430. DOI: https://doi.org/10.1016/S0893-6080(00)00026-5.
4. Indyk S. V., Lysechko V. P. (2020) The formation method of complex signals ensembles with increased volume based on the use of frequency bands. Management systems, navigation and communication. Poltava: National University "Poltava Polytechnic Institute n.a. Yuri Kondratiuk", V. 4(62), 2020, pp. 119-121. DOI: https://doi.org/10.26906/SUNZ.2020.4.119.
5. Indyk S. V., Lysechko V. P., Kulagin D. O., Zhuchenko O. S., Kovtun I. V. (2022) The study of the cross-correlation properties of complex signals ensembles obtained by filtered frequency elements permutations. Radio Electronics, Computer Science, Control. National University «Zaporizhzhia Polytechnic», Issue 2 (61), 2022, pp. 15-23. DOI: https://doi.org/10.15588/1607-3274-2022-2-2.
6. Jajodia B., Mahanta A., Ahamed S. R. (2020) IEEE 802.15.6 WBAN Standard Compliant IR-UWB Time-Hopping PPM Transmitter using SRRC signaling pulse. AEU – International Journal of Electronics and Communications, Volume 117, April 2020, 153119. DOI: https://doi.org/10.1016/j.aeue.2020.153119.
7. McNeill S. I. (2016) Decomposing a signal into short-time narrow-banded modes. Journal of Sound and Vibration, Volume 373, 7 July 2016, pp. 325-339. DOI: https://doi.org/10.1016/j.jsv.2016.03.015.
8. McNeill S. I., Zimmerman D. C. A framework for blind modal identification using joint approximate diagonalization. Mechanical Systems and Signal Processing, Volume 22, Issue 7, October 2008, pp. 1526-1548. DOI: https://doi.org/10.1016/j.ymssp.2008.01.010.
9. Nazari M. et al. (2020) Successive variational mode decomposition. Signal Processing, Volume 174, September 2020, 107610. DOI: https://doi.org/10.1016/j.sigpro.2020.107610.
10. Perets K., Lysechko V., Komar O. (2024) Modeling Nonlinear Signal Components Based on Volterra Series in the Frequency Domain during Spectral Reconstruction. Computer-integrated technologies: education, science, production.

Telecommunications and radio engineering. Lutsk, 2024. № 57, pp. 192-201. DOI: https://doi.org/10.36910/6775-2524-0560-2024-57-23.
11. Sun Y., Wanget P. et al. (2022) Principle and Performance Analysis of the Levenberg-Marquardt Algorithm in WMS Spectral Line Fitting. MDPI Photonics, December 2022, 9(12), 999. DOI: https://doi.org/10.3390/photonics9120999.
12. Tsagkaris K., Katidiotis A., Demestichas P. (2008) Neural network-based learning schemes for cognitive radio systems. Computer Communications, September 2008, 31(14), pp. 3394-3404, DOI: https://doi.org/10.1016/j.comcom.2008.05.040.
13. Wang Z., Chen Z., Xia B., Luo H. (2016) Modeling and bandwidth allocation of cognitive relay networks. In Proceedings of the 2016 IEEE/CIC International Conference on Communications in China (ICCC), 2016, pp. 1-6 DOI: https://doi.org/10.1109/ICCChina.2016.7636882.
14. Yang D. P., Song D. F., Zeng X. H., Wang X. L., Zhang X. M. (2022) Adaptive nonlinear ANC system based on time-domain signal reconstruction technology. Mechanical Systems and Signal Processing, Volume 162, 1 January 2022, 108056. DOI: https://doi.org/10.1016/j.ymssp.2021.108056.
15. Yang W.-X. (2008) Interpretation of mechanical signals using an improved Hilbert–Huang transform. Mechanical Systems and Signal Processing, Volume 22, Issue 5, July 2008, pp. 1061-1071. DOI: https://doi.org/10.1016/j.ymssp.2007.11.024.
16. Zhou W., Feng Z (2022) Empirical Fourier decomposition: An accurate signal decomposition method for nonlinear and non-stationary time series analysis, Mechanical Systems and Signal Processing, Volume 163, 15 January 2022, 108155. DOI: https://doi.org/10.1016/j.ymssp.2021.108155.
17. Indyk S. V., Lysechko V. P. (2020) Method of performing intervals taking into account the inter-correlation properties of segments. Management systems, navigation and communication. Poltava: National University "Poltava Polytechnic Institute n.a. Yuri Kondratiuk", V. 3 (61), 2020, pp. 128-130, DOI: https://doi.org/10.26906/SUNZ.2020.3.128.