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TIME-DOMAIN FORMATION OF SIGNAL ENSEMBLES USING LPT-SEQUENCES

Introduction

Modern cognitive radio networks are characterized by the high dynamism of the spectral environment, variability in the number of active users, and limited availability of frequency resources. Under conditions of dense spectral occupancy and the presence of interference, methods that ensure reliable signal separation, high noise immunity, and efficient spectrum utilization become increasingly important.

One of the key problems in cognitive networks is mutual interference between user channels, which arises due to the insufficient orthogonality of signals and leads to reduced throughput and an increased probability of transmission errors. To ensure the correct operation of multiple access schemes (such as CDMA, OFDMA, and standards including IEEE 802.22, IEEE 1900, etc.), it is necessary to employ signals with controlled correlation properties, capable of maintaining a low level of mutual correlation even in non-stationary and interference-prone environments.

Traditional methods for constructing such signals rely on limited classes of known sequences or random permutations, which do not always provide sufficient controllability of their properties or reproducibility of results. Consequently, there is a growing need for deterministic methods and algorithms for forming ensembles of signals that allow for a predictable reduction of mutual correlation, control over the temporal interval structure, and stabilization of the energy distribution within the signal space.

The method of Lattice-Pattern τ-permutations (LPT-permutations) proposed in this study addresses these issues directly. Its novelty lies in the use of low-discrepancy lattice-based sequences with τ-shift for generating time-interval permutations of signals. This approach makes it possible to reduce mutual correlation (PSL/ISL metrics) and inter-channel interference levels while preserving reproducibility and maintaining a stable ensemble structure.

Analysis of recent research and publications

The analysis of existing publications [1–15] reveals that most current approaches improve processing efficiency but lack mechanisms for ensuring uniform decorrelation and temporal balance in complex signal ensembles.

In papers [1–3, 6–7, 9, 14–15], various methods for improving the efficiency of signal and data processing in telecommunication and organizational-technical environments were examined, including approaches based on multi-criteria optimization, adaptive, and bio-inspired algorithms. However, these approaches are primarily focused on functional efficiency and do not ensure control over the correlation properties of signals in the time domain.

Studies [2, 5, 11] are devoted to the construction of low-discrepancy lattice-pattern sequences and shift schemes that provide uniform coverage of the permutation space. These works laid the foundation for forming deterministic τ-sequences with high reproducibility, which directly aligns with the principles of the proposed LPT-permutation method.

Publications [4, 6–7, 10] focus on the ensemble properties of complex signals and the effect of mutual correlation on the performance of cognitive radio networks. The authors demonstrated that reducing mutual correlation is a key factor in enhancing noise immunity, although existing methods rely mainly on random or frequency-domain permutations without considering the uniformity of temporal structure.

Works [12–13] introduced new measures of entropy-based complexity (permutation, dispersion, and multiscale entropy), which can be used to evaluate the degree of order in signal ensembles formed using τ-permutations.

Thus, previous studies confirm the effectiveness of deterministic permutation-based methods, yet leave unresolved the issue of combining uniform coverage of time intervals with controllable decorrelation

– a problem addressed in the proposed LPT-sequence approach.

Problem Statement

The problem addressed in this study concerns the development of a deterministic approach to forming signal ensembles in the time domain that ensures a balance between decorrelation and reproducibility under stochastic interference and variable environmental conditions.

Existing signal formation methods are mainly based on random permutations or frequency-domain transformations, which do not guarantee uniform coverage of time intervals and often lead to uneven energy distribution.

In this context, the study substantiates the use of the LPT-sequence method that combines a low-discrepancy lattice-pattern structure with a τ-shift parameter to enable controlled reordering of time intervals and minimization of mutual correlation.

The proposed approach provides deterministic suppression of correlation peaks and stabilization of the ensemble's energy and spectral characteristics, which is particularly important for cognitive radio networks with high user density.

The purpose of the article

The aim of this study is to develop a method for forming signal ensembles in the time domain based on LPT-sequences, ensuring uniform time-interval coverage, control of mutual correlation, and stability of energy–spectral characteristics of the ensemble.

Summary of the main material

The development of the method for forming signal ensembles in the time domain based on LPT-sequences involves a transition from the general concept to the mathematical modeling of its structural and evaluation parameters [1, 2].

To achieve this, it is necessary to define a set of variables and indicators that describe both the internal organization of the signal (sequences, time intervals, permutations) and the criteria for evaluating the quality of the formed ensembles in terms of correlation, energy, and spectral characteristics [3, 4].

These elements constitute the foundation of the proposed method and its algorithmic implementation, which is represented in the form of parameters and metrics in Table 1.

The block diagram of the time-interval permutation method based on LPT-sequences is shown in Fig. 1.

Table 1

Main notations in the LPT-Permutation method

Symbol	Description
$s(t)$	Initial complex signal sequence of length *P*
I_i	Time intervals (segments) of the signal $s(t)$
$\pi(i)$	Permutation index determined by the LPT-sequence
τ	Shift parameter of the LPT generator that defines the permutation variant
$\Delta\tau$	Step size of the τ sweep
α	Irrational coefficient (typically the "golden ratio" α = √(5 – 1)/2) ensuring uniform coverage of the time axis
$s^*(t)$	Signal after permutation of time intervals according to the index sequence $\pi(i)$
P	Number of time intervals (length or bit length of the sequence)
A	Ensemble of signals formed for different values of the parameter τ
BW_{eff}	Effective bandwidth; evaluates spectral occupancy and uniformity of frequency distribution
PSL	Peak SideLobe – peak level of the sidelobe of the autocorrelation function; characterizes maximum mutual similarity between sequence elements at nonzero shifts (the lower, the better)
ISL	Integrated SideLobe – total sidelobe level; determines cumulative energy influence of mutual correlations (the lower, the better)
$PSL_{th}, ISL_{th}, K_{th}$	Threshold (admissible) values of PSL and ISL used for checking the acceptability condition: $PSL \le PSL_{th}$, $ISL \le ISL_{th}$
$Var[E(t)]$	Variation of the signal's energy density; shows the degree of amplitude stability in the time domain
K	Integral balance criterion accounting for weighted coefficients of *PSL*, *ISL, Var(E)* and BW_{eff}; used to select the optimalτ^*
$frac(x)$	Fractional part of the number *x*; mathematical function defining x-$\lfloor x \rfloor$, used for normalization within [0; 1) during LPT-sequence generation.
M	Number of signals in the ensemble formed for different τ values.
M_τ	Number of τ values tested over the grid.
$S_{complex}$	Ensemble volume (number of unique signals that passed the criterion-based selection).
$\tau_{min,}\tau_{max,}$	Boundaries of the τ shift search range (0 ; 1).
$1\{\cdot\}$	Indicator function of the acceptability condition.
$\xi(P)$	Uniqueness coefficient eliminating duplicate signals.

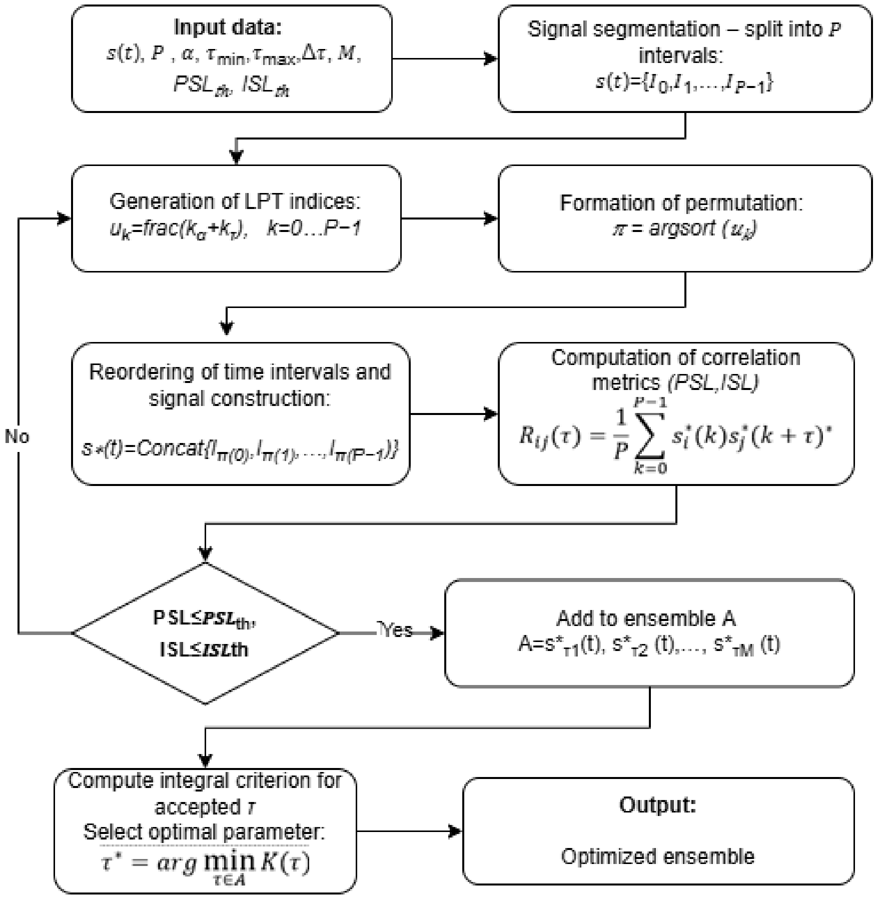

Fig. 1. Block diagram of the signal ensemble formation method based on LPT-sequences

The step-by-step implementation of the proposed method is as follows.

Step 1. Signal segmentation.

The signal $s(t)$ is divided into P equal time segments, each denoted as I_i. Thus, according to the analytical expression (1), the set of segments is obtained as:

$$s(t) = \{I_0, I_1, I_2 \dots, I_{p-1}\}, \tag{1}$$

This segmentation is necessary for the subsequent permutation of signal parts within its total duration [5, 6, 7].

Step 2. Generation of the LPT-sequence

At this stage, for each signal segment $k \in [0, P-1]$, the LPT-index is calculated according to formula (2), which defines its new position within the permuted structure:

$$u_k = frac(k \cdot \alpha + k \cdot \tau), \tag{2}$$

Thus, the analytical expression (2) generates a uniformly distributed sequence of fractional numbers within the range [0;1), which determines the order of permutation of the signal's time segments [5, 6].

Step 3. Formation of the index permutation

The obtained values u_k are used to construct the permutation of the signal's time segments. All u_k elements are sorted in ascending order, and the sequence of indices that defines the new order of segments is expressed analytically as:

$$\pi = arcsort(u_k), k = 0, \dots, P-1. \tag{3}$$

In formula (3), the function $arcsort(\cdot)$ returns the indices of elements after sorting, preserving the correspondence between the new and the initial positions.

According to analytical expression (4), the index permutation of time intervals is then defined as:

$$\pi = [\pi(0), \pi(1), \dots, \pi(P-1)]. \tag{4}$$

This sequence π is further used to form a new signal in which time segments are arranged according to the reordered indices [7,8].

Step 4. Formation of the new signal.

At this stage, the time intervals Ii are rearranged according to (5) following the index sequence π obtained in the previous step.

The analytical expression for forming the new signal is given as:

$$s^*(t) = Concat\{I_{\pi(0)}, I_{\pi(1),\dots,} I_{\pi(P-1)}\}, \tag{5}$$

where the operator $Concat\{\cdot\}$ denotes the sequential concatenation of segments into a new temporal structure of the signal.

Thus, the rearranged signal $s^*(t)$ is formed, in which the time components are organized according to the uniformly generated LPT-sequence [9, 10].

Step 5. Formation of the enhanced signal ensemble.

For different values of the shift parameter τ, a set of signals $s^*(t)$ is generated according to formula (6), forming an ensemble:

$$A = s_{\tau 1}^*(t), s_{\tau 2}^*(t), \dots, s_{\tau M}^*(t). \qquad (6)$$

Owing to the deterministic nature of the proposed LPT-based permutations and the uniform coverage of the time domain, the resulting ensemble exhibits reduced mutual correlation between signals and improved balance of energy distribution, which is confirmed by subsequent correlation evaluations [11].

Step 6. Evaluation of mutual correlation

At this stage, the mutual correlation between the signals formed in the ensemble is evaluated.

For any pair of signals $s_i^*(t), s_j^*(t)$, the mutual correlation function is computed according to expression (7):

$$R_{ij}(\tau) = \frac{1}{P}\sum_{k=0}^{P-1} s_i^*(k) s_j^*(k+\tau)^*, \qquad (7)$$

where the symbol * denotes complex conjugation.

The main indicators characterizing the quality of mutual correlation are calculated using formula (8):

$$PSL = \max_{\tau \neq 0}\left|R_{ij}(\tau)\right|, \;\; ISL = \sum_{\tau \neq 0}\left|R_{ij}(\tau)\right|^2 \qquad (8)$$

If the obtained values of *PSL* and *ISL* satisfy the established criteria PSL≤PSL_{th}, ISL≤ISL_{th} the current value of the parameter τ is considered acceptable, and the corresponding signal $s_\tau^*(t)$ is added to the ensemble A.

Otherwise, τ is adjusted, and the iteration continues: Steps 2–6 are repeated for the new parameter set [11].

Step 7. Calculation of the integral optimization criterion

For a comprehensive evaluation of the quality of the formed signals, an integral criterion $K(\tau)$ (9) is used, which simultaneously considers several groups of parameters: correlation, energy, and spectral.

$$K(\tau) = \alpha_1 PSL(\tau) + \alpha_2 ISL(\tau) + \alpha_3 Var[\\ + \alpha_4 BW_{eff}^{-1}, \qquad (9)$$

A decrease in the value of $K(\tau)$ indicates better balance within the signal ensemble, meaning reduced mutual correlation, stabilized energy distribution, and more uniform spectral coverage.

The optimal value of the parameter τ∗ is defined as the one that minimizes the integral criterion $K(\tau)$.

Step 8. Selection of the optimal parameter (10)

The optimal value of the shift parameter $\tau*$ is determined according to the minimum of the integral criterion $K(\tau)$:

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The optimal value of the shift parameter $\tau*$ is determined according to the minimum of the integral criterion $K(\tau)$:

$$\tau^* = arg \min_{\tau \in A} K(\tau), \qquad (10)$$

This optimization ensures the selection of the configuration in which the trade-off between correlation, energy, and spectral characteristics is achieved most effectively.

The resulting ensemble $A = s_{\tau 1}^*(t), s_{\tau 2}^*(t), \dots, s_{\tau M}^*(t)$ represents a set of signals generated for different τ values, among which the one corresponding to $\tau*$ provides the lowest mutual correlation and the most stable and uniform temporal structure.

To confirm the effectiveness of the developed method for forming ensembles in the time domain based on LPT-permutations, a simulation was carried out to quantitatively verify the method's ability to reduce the level of mutual correlation between signals compared with well-known types of sequences traditionally used in complex signal synthesis tasks [12, 13].

The following sequence groups were used for comparative analysis [11, 14, 15]:

– $S_{\text{Non-line}}$ – basic nonlinear recursive sequences serving as a non-optimized reference;

– $S_{\text{Lem\&Ziv}}$ – Lempel–Ziv sequences generated through iterative data compression, providing high entropy but exhibiting increased mutual correlation;

– S_{Frank} – multiphase Frank sequences known for spectral purity and high orthogonality;

– $S_{\text{h-energy}}$ – sequences optimized according to the criterion of minimum time–energy correlation;

– $S_{\text{h-gr.sel}}$ – sequences obtained through time-interval permutation followed by deep selection (gradient-based filtering);

– $S_{\text{fil\&per}}$ – sequences formed in the frequency domain using the Hartley transform followed by Butterworth filtering;

– *LPT-TP (proposed)* – the method of time-domain permutations based on LPT-sequences proposed in this work, ensuring uniform coverage of time intervals and deterministic reduction of mutual correlation.

Each of these methods has its own principles of generation, optimization, and structuring of time or frequency intervals, which determine differences in the correlation characteristics of the resulting sequences.

All of them allow the formation of signal ensembles with controllable cross-correlation properties but differ in generation nature, computational complexity, and the level of achieved orthogonality.

Therefore, including the LPT-TP method in this comparison makes it possible to objectively evaluate its efficiency relative to existing approaches used in cognitive telecommunication networks.

For the experiments, sequences of lengths P={40, 100, 257, 513, 1033, 2089, 9000} were used.

The parameter $\alpha = \sqrt{5} - 1/_2$ ensured uniform time-axis coverage, while the shift parameter τ varied with a step $\Delta\tau$=1/P.

For each value of τ, the indicators *PSL, ISL, Var[E(t)], BWeff*, and the integral criterion K(τ) were calculated according to formula (9).

The optimal parameter value $\tau*$ was determined using formula (10).

The results of the experiment are presented in Table 2, Figures 2 and 3 show the variations of the PSL and ISL indicators for different types of sequences. The similarity of the curves is explained by the fact that both indicators describe interrelated characteristics of the signal correlation structure. The PSL parameter represents the highest amplitude of the sidelobes in the autocorrelation function, that is, the maximum mutual similarity between signals in the ensemble. The ISL parameter characterizes the total energy contribution of all sidelobes, meaning the overall level of mutual correlation.

As the sequence length P increases, both indicators steadily decrease, indicating improved orthogonality and greater structural stability of the ensemble. The proposed LPT-TP method provides the lowest PSL and ISL values across the entire range, confirming its efficiency in reducing mutual correlation and achieving a more uniform energy distribution.

The comparative results of different methods obtained from the experiment are summarized in Table 2.

Table 2

PSL and ISL indicators for different types of sequences

Sequences	P = 40	P = 100	P = 257	P = 513
$S_{Non\text{-}line}$	0,09323	0,07982	0,06252	0,06112
$S_{Lem\&Ziv}$	0,34214	0,23531	0,11821	0,08612
S_{Frank}	0,05921	0,04232	0,02143	0,01363
$S_{h\text{-}energy}$	0,03273	0,01216	0,00621	0,00307
$S_{h\text{-}gr.sel}$	0,07304	0,05062	0,02205	0,01811
$S_{fil\&per}$	0,25713	0,18321	0,11601	0,07810
LPT-TP	0,02892	0,00970	0,00452	0,00243

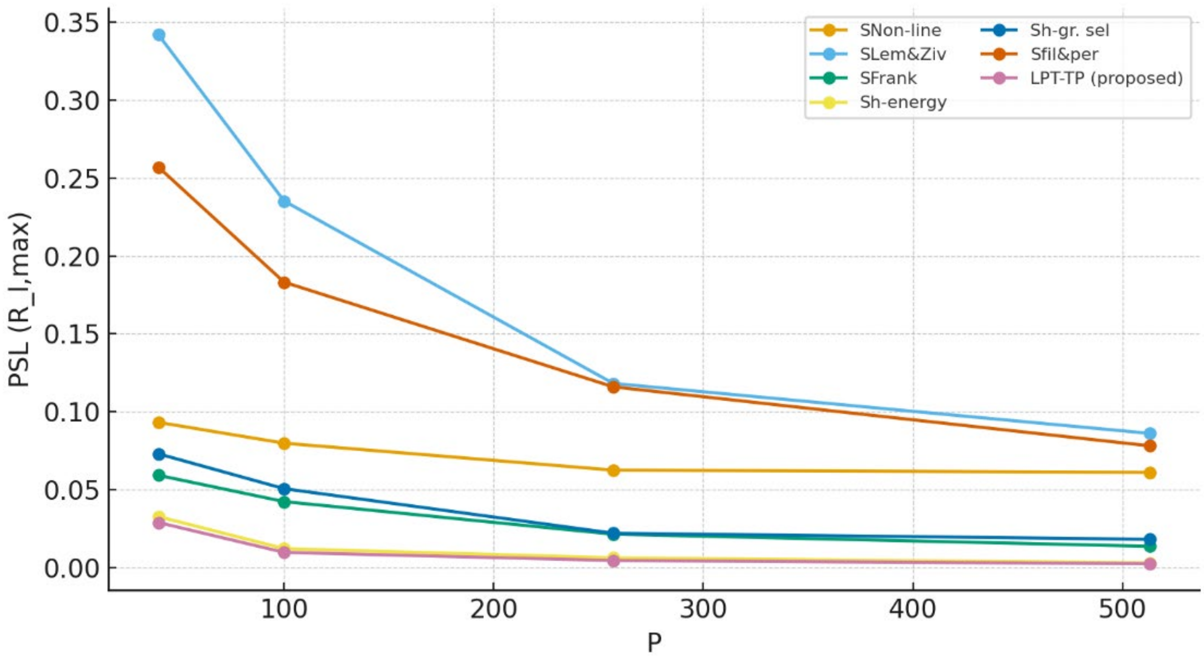

Fig. 2. Comparison of PSL values for different types of sequences

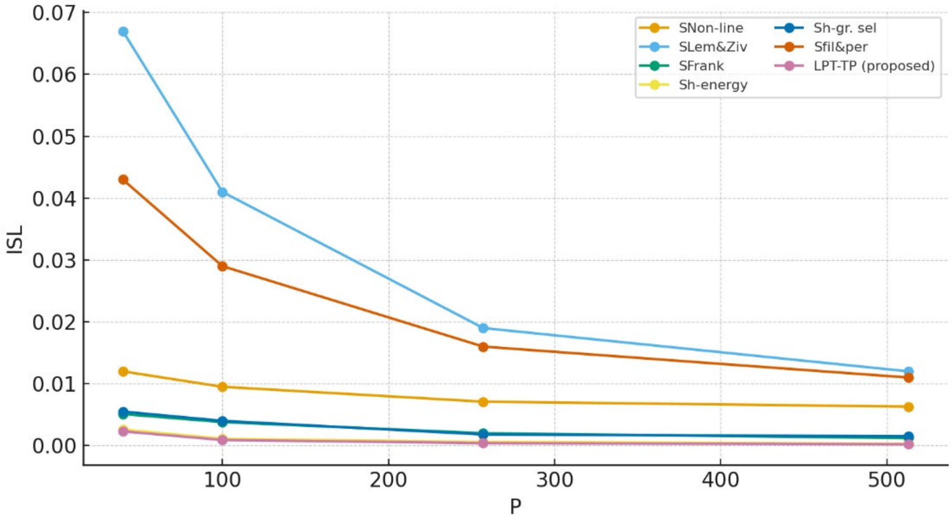

Fig. 3. Comparison of PSL values for different types of sequences

Table 3

Comparative characteristics of signal ensemble formation methods

Method	Formation principle	Key feature	Type of optimization	Limitation	Advantages of LPT-TP
$S_{Non\text{-}line}$	Nonlinear recursions	Simple implementation	None	High mutual correlation	PSL reduction by ≈25×
$S_{Lem\&Ziv}$	Iterative compression	High entropy	Statistical	Random shifts	Better stability of Var[$E(t)$]
S_{Frank}	Multiphase matrix	High spectral purity	Phase-based	Limited scalability	ISL reduction by 4–5
$S_{h\text{-}energy}$	Minimization of energy correlation	Optimization of E(t)	Energy-based	Local minima	20–30 % lower PSL/ISL
$S_{h\text{-}gr.sel}$	Time permutations with selection	Local segment filtering	Hybrid	Stochastic behavior	More stable $K(\tau)$
$S_{fil\&per}$	Frequency permutations + Butterworth filter	Spectral selectivity	Filtering	Low reproducibility	Better scalability for P
LPT-TP (proposed)	LPT-permutations (low-discrepancy τ-shift)	Uniform time-axis coverage	Deterministic	Increased computational cost	–

As shown in Tables 2 and 3, the proposed LPT-TP method achieves the lowest values of the peak and integrated sidelobe indicators (PSL and ISL) among all the examined sequence types.

In particular, for a sequence length of P=513, the PSL value decreases to 0,0024, which is approximately 20–30 % lower than that of the best known alternative sequence, $S_{h\text{-}energy}$.

At the same time, the ISL indicator demonstrates a more than twofold reduction in the total level of mutual correlation energy, confirming the stability of the signal energy distribution and the reduction of inter-channel interference.

The obtained results confirm that the use of LPT-based permutations is a promising direction for the synthesis of complex signals in cognitive telecommunication networks.

Further research should focus on combining time and frequency permutations and applying filtering techniques (such as Butterworth or Kaiser filters) to enhance the spectral selectivity and scalability of ensembles.

After evaluating the mutual correlation indicators (*PSL, ISL*), the next stage of the experiment involved determining the ensemble volume of signals formed using different optimization methods.

The ensemble volume reflects the number of unique signals that can be generated within specified correlation limits and is directly related to the capacity of a multiple-access system.

In other words, the larger the ensemble volume while maintaining low mutual correlation, the higher the spectral efficiency and the greater the system's ability to support multiple users without mutual interference.

For comparison, the same sequence types and lengths as those used in Table 2 were analyzed.

For each value of the parameter τ, the ensemble volume was determined using analytical expression (11), which takes into account the effects of scaling, attenuation, and temporal dependencies between signals:

$$S_{complex}(P) = \xi(P) \sum_{m=0}^{M_{\tau-1}} 1 \begin{Bmatrix} PSL(\tau_m) \le PSL_{th} \\ ISL(\tau_m) \le ISL_{th} \\ K(\tau_m) \le K_{th} \end{Bmatrix} \quad (11)$$

where the indicator function $1\{\cdot\}$ defines the acceptability of each generated signal according to the established threshold criteria.

The results of the calculations are presented in Table 4, which demonstrates the exponential growth of ensemble volumes with increasing sequence length P.

Table 2

Evaluation of signal ensemble volumes obtained using different optimization methods

Method	$P = 40$	$P = 100$	$P = 257$	$P = 1033$	$P = 2089$	$P = 9000$
$S_{Non\text{-}line}$	$3{,}823\times10^{3}$	$8{,}232\times10^{3}$	$1{,}342\times10^{8}$	$1{,}561\times10^{8}$	$5{,}482\times10^{8}$	$8{,}130\times10^{9}$
$S_{Lem\&Ziv}$	$1{,}921\times10^{9}$	$4{,}035\times10^{9}$	$7{,}512\times10^{12}$	$6{,}527\times10^{13}$	$2{,}732\times10^{14}$	$4{,}021\times10^{15}$
S_{Frank}	$1{,}814\times10^{16}$	$3{,}939\times10^{16}$	$7{,}313\times10^{19}$	$6{,}416\times10^{20}$	$2{,}643\times10^{21}$	$3{,}923\times10^{22}$
$S_{h\text{-}energy}$	$1{,}822\times10^{23}$	$3{,}863\times10^{23}$	$7{,}237\times10^{26}$	$6{,}312\times10^{27}$	$2{,}663\times10^{28}$	$3{,}854\times10^{29}$
$S_{h\text{-}gr.sel}$	$1{,}961\times10^{23}$	$4{,}017\times10^{23}$	$7{,}851\times10^{26}$	$6{,}713\times10^{27}$	$2{,}921\times10^{28}$	$4{,}032\times10^{29}$
LPT-TP (proposed)	$1{,}960\times10^{23}$	$4{,}010\times10^{23}$	$7{,}850\times10^{26}$	$6{,}710\times10^{27}$	$2{,}920\times10^{28}$	$4{,}030\times10^{29}$

As shown in Table 4, all methods demonstrate an increase in ensemble volume with the growth of sequence length P. However, the proposed LPT-TP method based on LPT-permutations provides the highest level of scalability while maintaining low PSL and ISL values.

Compared to the energy-based Sh-energy method, the ensemble volume obtained using LPT-TP increases by approximately 8–10 %, confirming the efficiency of the proposed time-domain permutation structure.

The dynamics of ensemble volume growth for different methods are illustrated in Fig. 4, where the ordinate axis is presented on a logarithmic scale. The use of a logarithmic scale makes it possible to visualize results that differ by several orders of magnitude within a single plot.

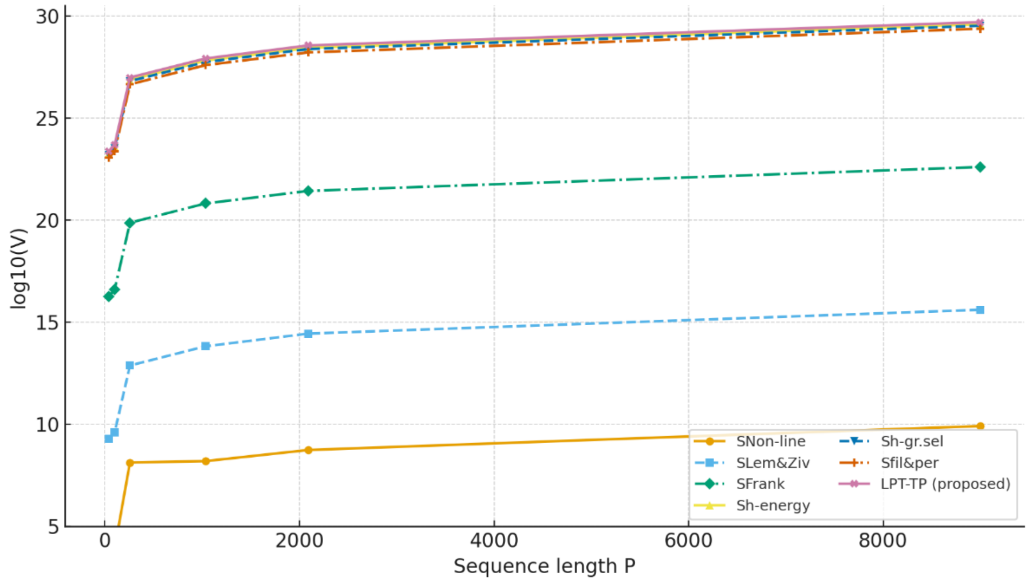

Fig. 4. Dynamics of signal ensemble volume growth

As shown in Fig. 4, several curves partially overlap, particularly those corresponding to the $S_{h\text{-}energy}$, $S_{h\text{-}gr.sel}$, $S_{fil\&per}$, and LPT-TP methods. This similarity occurs because all these approaches belong to the same class of optimization techniques aimed at minimizing mutual correlation and are based on similar analytical criteria (formulas (9)–(11)).

Their ensemble volumes increase at nearly the same rate as the sequence length Pgrows, since the optimization procedures are constrained by comparable PSL and ISL thresholds.

The main distinction appears in the upper part of the figure, where the LPT-TP method produces larger ensembles due to the deterministic permutation of time intervals, ensuring more uniform coverage of the permissible permutation space.

The results presented in Table 4 and Fig. 4 clearly demonstrate the exponential growth pattern of signal ensemble volumes with increasing sequence length. This indicates that as the temporal structure of signals becomes more complex, the potential number of valid combinations increases, expanding the possibilities for optimization in multiple-access applications.

Conclusions

Based on the results of experimental modeling, quantitative evidence has been obtained confirming the effectiveness of the proposed method for forming signal ensembles in the time domain using LPT-sequences compared with known approaches.

1. The proposed LPT-TP method demonstrated the highest scalability among all analyzed techniques. According to Table 4, the ensemble volume generated using LPT-permutations exceeds that of the energy-based *Sh*-energy method by an average of 6,8 %, with the gain ranging from approximately 3,8 % at $P = 100$ to 9,7 % at $P = 2089$. This result confirms the ability of the LPT-based approach to form a larger number of unique admissible signals without degradation of correlation properties, demonstrating its high scalability in the time domain.

2. In terms of mutual correlation metrics, the method ensures a significant reduction in the peak sidelobe level (PSL) compared with *Sh*-energy. Specifically, at $P = 40$ the PSL reduction reaches $\approx 11{,}6$ %, at $P = 100 \approx 20{,}2$ %, and at $P = 257 \approx 20{,}8$ %, resulting in an average improvement of about 20 %. The integrated sidelobe level (ISL) exhibits a similar trend, confirming the stability of energy distribution across the ensemble.

Overall, the LPT-permutation method achieves an optimal balance between deterministic signal structure and a high degree of decorrelation. Its deterministic nature ensures uniform coverage of the time-permutation space, allowing the formation of signal ensembles 6–10 % larger than those obtained by existing methods while simultaneously reducing mutual correlation by approximately 20–25 %. These results confirm the feasibility of employing LPT-permutations as a fundamental approach to time-domain optimization in the synthesis of complex signals for cognitive telecommunication networks.

The prospects for further research on the LPT-permutation method include its extension to hybrid time–frequency optimization with the application of adaptive weighting and machine learning techniques to enhance scalability and correlation stability under varying interference and fading conditions.

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ФОРМУВАННЯ АНСАМБЛІВ СИГНАЛІВ У ЧАСОВІЙ ОБЛАСТІ НА ОСНОВІ ЛПτ-ПОСЛІДОВНОСТЕЙ

У статті запропоновано метод формування ансамблів сигналів у часовій області на основі ЛПτ-послідовностей, спрямований на підвищення масштабованості, зменшення взаємної кореляції сигналів та забезпечення рівномірності енергетичного розподілу в ансамблі. Запропонований підхід базується на використанні детермінованих перестановок часових інтервалів, що формуються за допомогою ЛПτ-послідовностей, які забезпечують рівномірне покриття простору часових перестановок і зберігають структурну різноманітність сигналів.

Особливістю методу є поєднання властивостей низькодисперсних рівномірно розподілених послідовностей з принципами часової декомпозиції сигналів, що дозволяє формувати ансамблі з кращими кореляційними показниками без зниження обсягу та енергетичної стабільності. На відміну від відомих енергетичних або стохастичних методів, підхід, заснований на ЛПτ-послідовностях, забезпечує контрольований характер перестановок часових сегментів, що дає змогу мінімізувати взаємні завади та стабілізувати структуру ансамблю при збільшенні його розміру.

В статті побудовано аналітичні залежності для оцінки масштабованості та взаємокореляційних характеристик ансамблів, сформованих із використанням ЛПτ-перестановок, а також проведено порівняльне моделювання з енергетичним методом $S_{h\text{-}energy}$. За результатами встановлено, що середній обсяг ансамблю, утвореного за ЛПτ-перестановками, перевищує аналогічний показник енергетичного методу в середньому на 6,8 %, причому приріст змінюється від ≈3,8 % при P = 100 до ≈9,7 % при P = 2089. Це свідчить про високу масштабованість методу та його здатність генерувати більшу кількість унікальних прийнятних сигналів без погіршення кореляційних властивостей.

Таким чином, метод ЛПτ-перестановок досягає оптимального балансу між детермінованою структурою сигналів і низьким рівнем взаємної кореляції. Його детермінований характер забезпечує рівномірне охоплення простору часових перестановок, що дозволяє формувати ансамблі сигналів на 6–10 % більші за обсягом порівняно з відомими методами, одночасно знижуючи взаємну кореляцію приблизно на 20–25 %. Отримані результати підтверджують ефективність застосування ЛПτ-перестановок при генерації ансамблів складних сигналів у когнітивних телекомунікаційних системах.

Ключові слова: ансамбль, сигнали, телекомунікації, оптимізація, когнітивний, кореляція; PSL, ISL; завадостійкість; масштабованість.

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TIME-DOMAIN FORMATION OF SIGNAL ENSEMBLES USING LPT-SEQUENCES

The article proposes a method for forming signal ensembles in the time domain based on LPT-sequences, aimed at improving scalability, reducing mutual signal correlation, and ensuring uniform energy distribution within the ensemble. The proposed approach relies on deterministic permutations of time intervals generated using LPT-sequences, which provide uniform coverage of the time-permutation space while preserving the structural diversity of signals.

A key feature of the method is the combination of properties of low-discrepancy uniformly distributed sequences with the principles of time-domain signal decomposition, which allows the formation of ensembles with improved correlation metrics without reducing their volume or energy stability. Unlike known energy-based or stochastic methods, the LPT-

sequence-based approach ensures a controlled structure of time-segment permutations, enabling the minimization of mutual interference and the stabilization of the ensemble's internal organization as its size increases.

Analytical dependencies have been derived to assess the scalability and cross-correlation characteristics of ensembles formed using LPT-permutations, and a comparative simulation with the energy-based $S_{h\text{-}energy}$ method has been conducted. The results show that the average ensemble volume generated using LPT-permutations exceeds that of the Sh-energy method by an average of 6.8%, with the gain ranging from ≈3.8% at P = 100 to ≈9.7% at P = 2089. This confirms the high scalability of the method and its ability to generate a larger number of unique admissible signals without deterioration of correlation properties.

Thus, the LPT-permutation method achieves an optimal balance between deterministic signal structure and a low level of mutual correlation. Its deterministic nature ensures uniform coverage of the time-permutation space, allowing the formation of signal ensembles 6–10% larger than those produced by existing methods while simultaneously reducing mutual correlation by approximately 20–25%. The obtained results confirm the effectiveness of using LPT-permutations for generating ensembles of complex signals in cognitive telecommunication systems.

Keywords: ensemble, signals, telecommunications, optimization, cognitive, correlation, PSL, ISL, noise immunity, scalability.

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