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THE METHOD OF FORMING ENSEMBLES OF COMPLEX SIGNALS BASED ON MULTI-SCALE DECOMPOSITION OF TIME INTERVALS AT DIFFERENT LEVELS OF DETAIL

Bershov V., Yakymchuk N. The method of forming ensembles of complex signals based on multi-scale decomposition of time intervals at different levels of detail. This article addresses the challenges of forming signal ensembles in dynamic cognitive radio environments, focusing on the limitations of traditional methods. The study proposes a new approach based on multiscale time interval decomposition, which allows for the creation of signal ensembles at varying levels of temporal detail. The key innovation of this method is its ability to improve signal reproduction accuracy, reduce inter-symbol and inter-channel interference, and enhance the overall efficiency of data processing. The method's adaptability to changing environmental conditions is also a core advantage, enabling better use of bandwidth and reduced transmission delay. Through the decomposition of time intervals into coarse, intermediate, and fine levels, this method allows for the detailed analysis of short-term, medium-term, and long-term signal components. Experimental results demonstrate the superiority of this approach in terms of signal recovery accuracy, noise resilience, and processing speed. These findings highlight the potential for optimizing signal processing in cognitive radio networks, particularly in environments with high levels of noise and interference. Future research aims to integrate machine learning algorithms to further enhance adaptability in real-time scenarios.
Keywords: multiscale signal decomposition, cognitive radio environment, time intervals, adaptive algorithms, mean square deviation (MSE), signal-to-noise ratio (SNR), signal processing

Бершов В.С., Якимчук Н.М. Метод формування ансамблів складних сигналів на основі багатомасштабної декомпозиції часових інтервалів на різних рівнях деталізації. У статті розглядаються проблеми формування ансамблів сигналів систем передачі у динамічних середовищах когнітивного радіо, при цьому, увага акцентується на обмеженнях традиційних методів синтезу ансамблів сигналів. Дослідження пропонує новий підхід, заснований на багатомасштабній декомпозиції часових інтервалів, що дозволяє створювати ансамблі сигналів на різних рівнях часової деталізації. Ключовим нововведенням цього методу є підвищення точності відтворення сигналів, зменшення міжсимвольних та міжканальних завад, а також підвищення загальної ефективності обробки даних. Важливою перевагою запропонованого методу є його адаптивність до змінних умов навколишнього середовища, що дозволяє краще використовувати пропускну здатність та зменшувати затримки передачі. За допомогою виконання декомпозиції часових інтервалів на грубі, проміжні та точні рівні, цей метод дає змогу детально аналізувати короткострокові, середньострокові та довгострокові компоненти сигналу в телекомунікаційних трактах. Отримані експериментальні результати демонструють переваги підходу для покращення точності відновлення сигналу, стійкості до шуму та швидкості обробки. Отримані результати підкреслюють потенціал оптимізації обробки сигналів у когнітивних радіомережах, особливо в умовах високого рівня шуму та завад. Подальші дослідження спрямовані на інтеграцію алгоритмів машинного навчання для підвищення адаптивності в режимі реального часу.
Ключові слова: багатомасштабна декомпозиція сигналів, когнітивне радіосередовище, часові інтервали, адаптивні алгоритми, середньоквадратичне відхилення (MSE), співвідношення сигнал/шум (SNR), обробка сигналів.

Statement of a scientific problem.

Traditional methods of forming ensembles of complex signals in the modern dynamic cognitive radio environment demonstrate insufficient flexibility and adaptability, which creates the need to develop new methods that provide effective protection against inter-channel and inter-symbol interference, balance between indicators of signal volumes and the function of mutual correlation, have a high level of bandwidth indicators , low transmission delay and adaptability to changing environmental conditions.

One of these methods is the method of forming ensembles of complex signals based on multi-scale decomposition of time intervals, which allows creating ensembles of signals at different levels of temporal detail, increasing the volume of ensembles of complex signals and improving their characteristics, in particular, increasing the efficiency of processing in the time domain. Multiscale Decomposition is a signal analysis method that allows you to decompose a signal into components of different durations in order to identify and analyze long-term, medium-term and short-term components of a signal (Fig. 1).

1. The coarse level is responsible for detecting the main long-term components of the signal. The signal is divided into large time intervals that allow you to understand its general structure and trends. For example, the division can be made into intervals of 10 seconds if the signal is long, or into intervals of 1 second for shorter signals.

2. Intermediate level. After a rough breakdown, each large interval is detailed into medium-duration components. This allows you to detect changes and trends that were not visible at a coarse level. For example, intervals can be divided into smaller subintervals of 1 second (for long intervals) or 100 ms (for shorter intervals).

3. Subtle level. At this level of temporal segmentation, short-term pulses and signal variations are analyzed. Each average interval is detailed into small time segments, which allows you to detect rapid changes and impulses. For example, each average interval can be divided into subintervals of 10 ms or even less, depending on the nature of the signal.

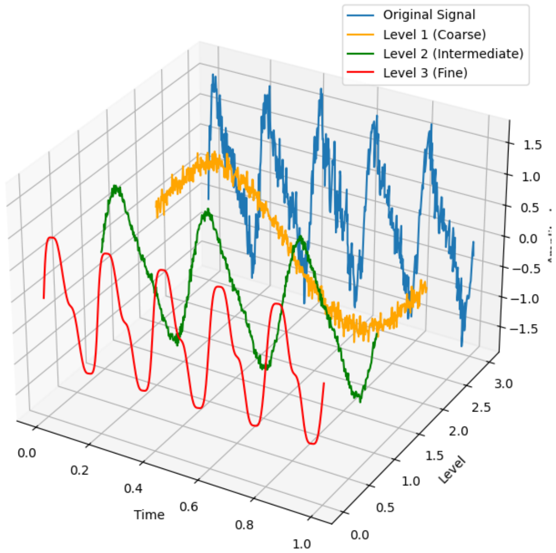


Fig. 1. Fragment of three-level multiscale decomposition

The feasibility of using the method lies in the fact that the method allows cognitive radio systems to flexibly and adaptively analyze signals in the time domain, and this contributes to more efficient use of available resources and improves the quality of data transmission. Thanks to accurate analysis and adaptive segmentation, the method optimizes data transmission, increases the efficiency of resource use even in conditions of high noise and interference.

Research analysis.

The analysis of existing domestic and foreign research on this subject [1-14] proved that a significant part of the work devoted to signal processing and cognitive radio networks is aimed at developing methods of increasing noise immunity, optimizing spectral characteristics, and improving the accuracy of signals in difficult conditions [1]. In particular, researchers proposed different approaches to time-frequency analysis, the use of wavelet transformations, adaptive algorithms and decomposition methods [2].

However, most of the works [3,5-11, 13] do not substantiate the creation of effective ensembles of complex signals based on multilevel decomposition, which allows improving the characteristics of signals and adapting them to changing conditions. Also, the integration of multiscale decomposition methods with adaptive algorithms that could automatically adjust signal processing parameters in real time, ensuring high efficiency in intelligent dynamic radio environments, has not been sufficiently investigated.

The purpose of the work.

The purpose of this study is to develop a method for forming ensembles of complex signals based on multi-scale decomposition of time intervals with different levels of temporal detail.

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

The effectiveness of the method of forming ensembles of complex signals based on multi-scale decomposition of time intervals at different levels of time detail is evaluated by indicators.

1. Accuracy of signal reproduction. The degree of deviation from the original signal is calculated, which is mathematically expressed as Mean Squared Error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x(t_i) - \hat{x}(t_i))^2, \quad (1)$$

where N – is the number of time points;
$x(t_i)$ – is the value of the original signal at the moment of time t_i;
$\hat{x}(t_i)$ – is the value of the reproduced signal at the moment of time t_i.

2. Resolution is the ability to divide the initial signal $x(t)$ into time segments. The indicator shows the ability of the method to detect and distinguish different components of the signal at different levels of temporal detail, which allows for detailed analysis. Calculations are made using the formula:

$$x(t) = \sum_{n=1}^{N} \left(\sum_{k=1}^{K} c_k^{(n)} \phi_k^{(n)}(t) \right), \tag{2}$$

where n – detail level number;
K – number of components per level n
$c_k^{(n)}$ – decomposition factor for component k at level n;
$\phi_k^{(n)}$ – basis function for component k at level n.

3. Calculation speed. It is estimated by the time T required for signal processing, taking into account the number of iterations I and the computational complexity of the algorithm $O(I)$. It is calculated according to the formula:

$$\mathrm{T} = \sum_{i=1}^{I} \mathrm{O}\ (\mathrm{i}), \tag{3}$$

4. Resistance to noise. A metric that shows the ability to maintain accuracy in the presence of noise. It is measured by the signal-to-noise ratio parameter (SNR):

$$SNR = 10 \log_{10} \left(\frac{\sum_{i=1}^{N} x(t_i)^2}{\sum_{i=1}^{N} (x(t_i) - \hat{x}(t_i))^2} \right), \tag{4}$$

5. Energy efficiency is estimated by the formula as the average value of the signal energy in time segments:

$$E = \frac{1}{N} \sum_{i=1}^{N} |x(t_i)|^2, \tag{5}$$

6. Correlation coefficient ρ. Determines the similarity between the average value of the original $\bar{x}$ and the reproduced $\bar{\hat{x}}$ signal according to the formula:

$$\rho = \frac{\sum_{i=1}^{N} (x(t_i) - \bar{x}) (\hat{x}(t_i) - \bar{\hat{x}})}{\sqrt{\sum_{i=1}^{N} (x(t_i) - \bar{x}(t_i))^2 \sum_{i=1}^{N} (\hat{x}(t_i) - \hat{x})^2}}, \tag{6}$$

7. The cross-correlation function. Allows you to assess how well the reproduced signal corresponds to the original one at different time shifts τ, the calculation formula:

$$R_{x_i x_j}(\tau) = \frac{1}{N-\tau} \sum_{i=1}^{N-\tau} x(t_i)\, \hat{x}(t_i + \tau), \tag{7}$$

where $R_{x_i x_j}(\tau)$ – shear cross-correlation functionτ;
$x(t_i)$ – the value of the original signal at the instant of time t_i;
$\hat{x}(t_i + \tau)$ – the value of the reproduced signal at the offset τ.

The generalized system of conditions for all levels of temporal detail can be written in the form of a system of equations:

$$\begin{cases} x(t) = \sum_{k=1}^{K_1} c_k^{(1)} \phi_k^{(1)}(t) + \epsilon^1(t), \text{де } \epsilon^1(t) \to 0 \text{ при } K_1 \to \infty \\ \epsilon^1(t) = \sum_{k=1}^{K_2} c_k^{(2)} \phi_k^{(2)}(t) + \epsilon^2(t), \text{де } \epsilon^2(t) \to 0 \text{ при } K_2 \to \infty \\ \epsilon^2(t) = \sum_{k=1}^{K_3} c_k^{(3)} \phi_k^{(3)}(t) + \epsilon^3(t), \text{де } \epsilon^3(t) \to 0 \text{ при } K_3 \to \infty \\ \Delta t_1 > \Delta t_2 > \Delta t_3 > 0, \text{де } \Delta t_1 - the\ length\ of\ the\ intervals \\ is\ 1,2,3\ levels \end{cases}, \quad (8)$$

where $\epsilon^R(t)$ – approximation errors at different levels.

Taking into account indicators and conditions, an algorithm for practical implementation of the method of forming ensembles of complex signals based on multi-scale time decomposition was developed. Let's consider its stages in more detail (Fig 2).

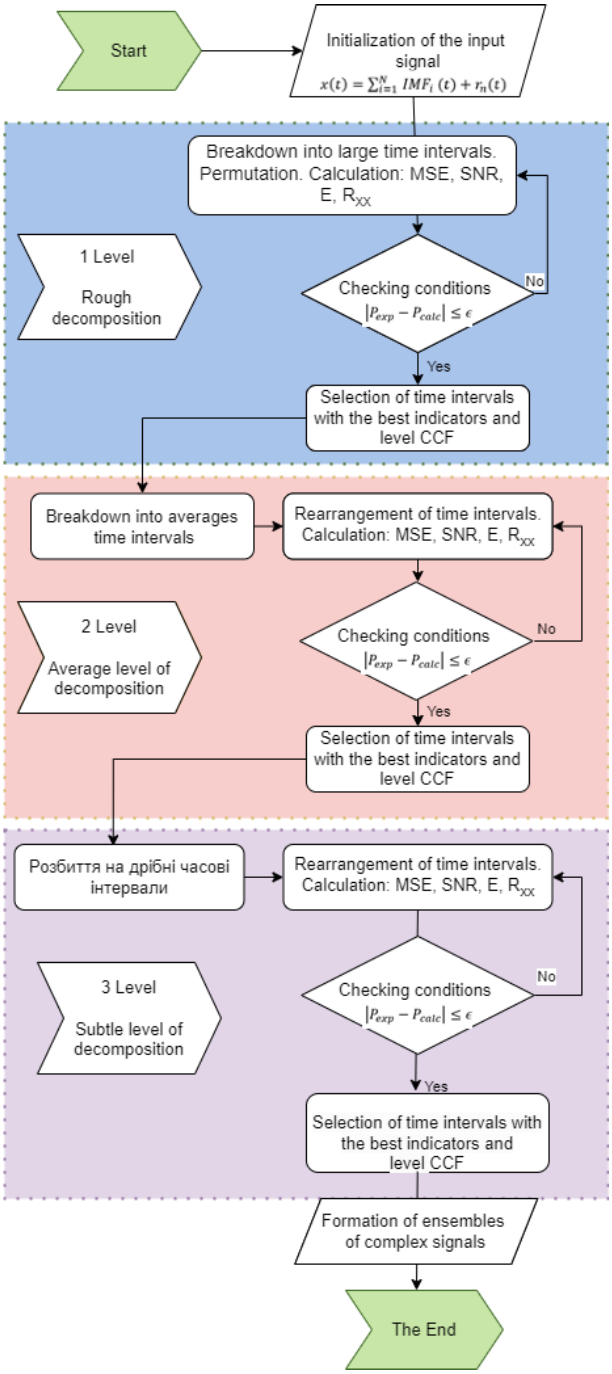


Fig. 2. Block diagram of the multiscale time decomposition algorithm

1 Stage. The beginning of the algorithm. Initialization of the input signal $x(t)$. The decomposition process is adapted to the specific properties of the input signals, which allows for maximum accuracy and efficiency of further processing. Decomposition (IMF) is carried out through an iterative process, which can be represented by the formula:

$$x(t) = \sum_{i=1}^{N} IMF_i\ (t) + r_n(t), \tag{9}$$

where $IMF_i\ (t)$ – internal modal functions; $r_n(t)$ – is the remainder.

2 Stage. A rough level of decomposition. At this stage, the ensemble of signals is broken down into large time intervals for further analysis. The input signal can be given in the form of an equation:

$$x(t) = \sum_{k=1}^{K_1} \left(\sum_{k=1}^{K} c_k^{(1)}\ \phi_k^{(1)}(t) + \epsilon^1(t) \right), \tag{10}$$

Time intervals are rearranged at each level of decomposition (coarse, medium, fine). The optimal permutations are chosen based on the assessment of the correlation properties of the signals. A pairwise calculation of the cross-correlation function (CCF) value is used to estimate the correlation properties.

3 Stage. At this stage, the accuracy and compliance of the indicators with the specified (experimental) conditions of minimum similarity for the coarse level of decomposition are checked. If the accuracy and conditions are met, it is possible to proceed to the intermediate level of decomposition. If the condition of minimum similarity is not fulfilled, the procedure is repeated with the correction of the intervals that give the greatest number of violations. In this case, we return to stage 2 and repeat the iteration. The condition of minimal similarity can be determined by the formula:

$$\left| P_{exp} - P_{calc} \right| \leq \epsilon, \tag{11}$$

where P_{exp}, P_{calc} – experimental and calculated indicators, respectively; ϵ – permissible deviation.

4 Stage. Average level of temporal decomposition. At this stage, the residual signal $\epsilon^1(t)$ is split into average time intervals, which allows for a more detailed analysis of the signal structure. The process can be written mathematically as:

$$\epsilon^1(t) = \sum_{k=1}^{K_2} c_k^{(2)} \phi_k^{(2)}(t) + \epsilon^2(t). \tag{12}$$

At the middle level of decomposition, a similar process takes place, as in stage 2, but with a more detailed breakdown of intervals. The evaluation indicators are also calculated, as for the rough level. This allows you to reveal additional features and characteristics of the signal that were not identified at the previous level of decomposition. At this stage, time intervals are also permuted with an assessment of the correlation properties of the signals and a pairwise calculation of the cross-correlation function (CCF).

For more accurate control of approximation errors and correlation properties, adaptive optimization methods or genetic algorithms can be used at this stage.

One of the most common adaptive optimization algorithms is the Least Mean Squares (LMS) algorithm. Initialize the weight vector $w(0)$ for each step n:

$$\begin{gathered} y(n) = w^T(n)x(n) \\ e(n) = d(n) - y(n) \\ w\ (n+1) = w\ (n) + \mu e(n)[x(n) \end{gathered}, \tag{13}$$

where $x(n)$ – vector of input data;
$y(n)$ – adaptive filter vector;
$d(n), e(n)$ – desired signal and error, respectively;
μ – algorithm step (learning ratio).

5 Stage. Checking the accuracy and compliance of indicators with the given conditions of minimum similarity. Step 5 is similar to step 3, with the difference that verification and correction are performed for the medium decomposition level rather than the coarse one. If the condition specified by the experiment is not fulfilled, the intervals that give the greatest number of violations are corrected, and the iteration is repeated.

6 Stage. Fine level of time decomposition. At this stage, the residual signal $\epsilon^2(t)$ is split into small time intervals for an even more detailed analysis than was the case at previous levels. Mathematically, this can be written as:

$$\epsilon^2(t) = \sum_{k=1}^{K_3} c_k^{(3)} \phi_k^{(3)}(t) + \epsilon^3(t) \tag{14}$$

Also, at a fine level, estimation indicators are calculated, time intervals are rearranged with a pairwise calculation of CCF, and the accuracy and compliance of the indicators obtained as a result of the calculations with the conditions of minimum similarity are checked.

7 Stage. Formation of ensembles of complex signals. At this stage, the sequences formed as a result of the three-level decomposition are used to form ensembles of complex signals. Thanks to the three-level decomposition, each sequence contains detailed information about the original signal, which allows you to display its characteristics as accurately as possible. In general, the generated signal can be written in the form:

$$x(t) = \sum_{k=1}^{K_1} c_k^{(1)} \phi_k^{(1)}(t) + \sum_{k=1}^{K_2} c_k^{(2)} \phi_k^{(2)}(t) + \sum_{k=1}^{K_3} c_k^{(3)} \phi_k^{(3)}(t) + \epsilon^3(t), \tag{15}$$

After combining all levels of decomposition, the consistency of the obtained sequences is checked by analyzing the correlation properties and checking for the presence of systematic errors, after which the final ensembles of complex signals are formed. Experimental studies were conducted to verify and validate the proposed method. The initial data of ensembles of complex signals used in the experiments are shown in table. 1.

Table. 1 Output data for Ensemble 1

Component	Amplitude (A)	Frequency (Fr)	Characteristic
Low frequency	A_1=1,0	Fr_1=1 Hz	Low-frequency sinusoidal signal
Medium frequency	A_2=0,5	Fr_2=5 Hz	Medium frequency sinusoidal signal
High frequency	A_3=0,2	–	High frequency signal
Impulses	A_4=0,8	T=0,2; 0,5; 1c	Pulses with different durations and breaks

Table. 2 Output data for Ensemble 2

Component	Amplitude (A)	Frequency (Fr)	Characteristic
Modulated signal	A_5=1,0	Fr_3=2 Hz Fr_4=0,5 Hz	Low-frequency modulated sinusoidal signal with phase modulation
High frequency noise	A_6=0,2	–	High frequency noise
Impulses	A_7=0,7	T=0,3;0,7;1.2 c	Pulses with different durations and breaks

At the first coarse level of multi-scale time decomposition, the initial division of signals into large time intervals takes place, each of which is analyzed separately. The optimal permutations of time intervals are chosen based on the evaluation of the correlation properties of the signals, which helps to increase immunity. The calculation of evaluation indicators according to the algorithm of the large-scale time decomposition method is presented in the table. 3-4.

Table 3 – Calculation of indicators of the coarse level of decomposition for Ensemble 1

Segment	MSE	SNR (dB)	Energy E	Correlation coefficient (ρ)	R_{xixj}
1	0,1005	9,861	40,22	0,891	0,789
2	0,1021	9,789	40,84	0,876	0,802
3	0,0987	10,002	39,48	0,894	0,812
4	0,1013	9,816	40,52	0,889	0,801
5	0,1030	9,755	41,20	0,883	0,798

Calculations show that Ensemble 1 shows a higher signal recovery accuracy compared to Ensemble 2. For Ensemble 1, the mean value (MSE) is about 0,1011, which proves the low error rate after signal recovery; the signal-to-noise ratio (SNR) is 9,845 dB, which shows a sufficiently high signal-to-noise level; the E energy is 40.45, indicating signal stability, and the correlation coefficient (ρ) is 0.887, demonstrating high similarity between the original and reconstructed signals.

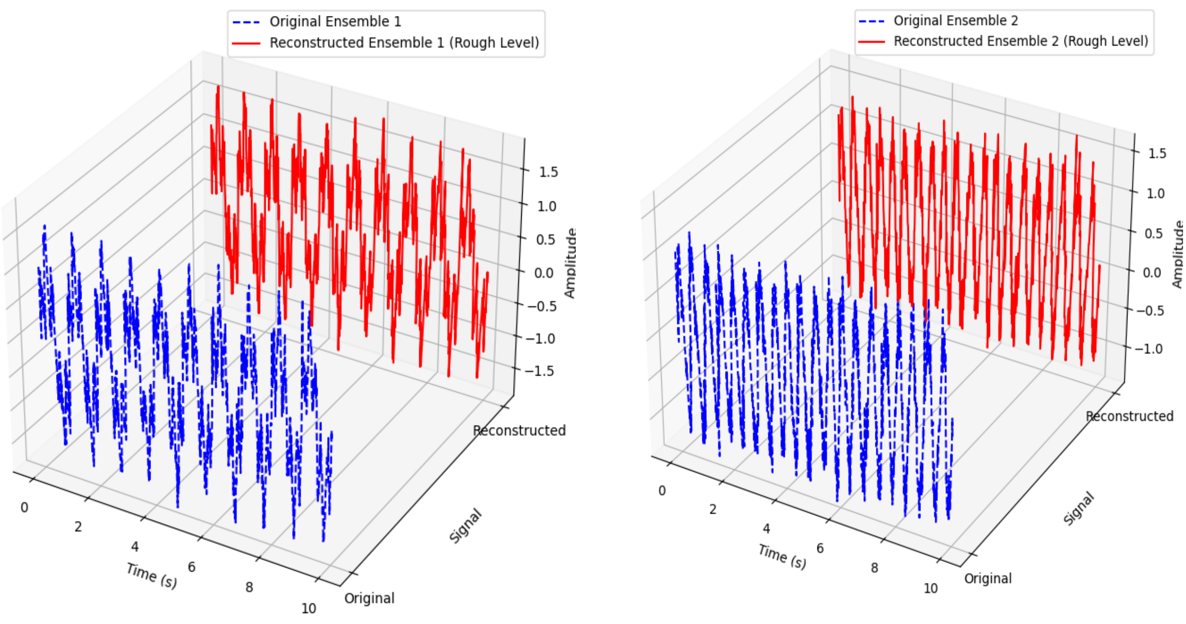
Rxиxj shows a value in the range of 0,789-0,812, which indicates an acceptable (conditionally, taking into account the given noises and disturbances, but far from orthogonality) mutual correlation between different segments. Such results testify to the effectiveness of the method in isolating and restoring the main components of the signal under the given influence of noise.

Table 4 – Calculation of indicators of the coarse level of decomposition for Ensemble 2

Segment	MSE	SNR (dB)	Energy E	Correlation coefficient (ρ)	R_{xixj}
1	0,1523	8,289	60,92	0,742	0,695
2	0,1495	8,379	59,80	0,751	0,702
3	0,1531	8,265	61,24	0,738	0,688
4	0,1507	8,342	60,28	0,747	0,691
5	0,1489	8,409	59,56	0,753	0,699

For Ensemble 2, the MSE is 0,1509, indicating a higher error rate after signal recovery compared to Ensemble 1; SNR – 8,337 dB, which shows a lower signal-to-noise ratio; E is 60,36, indicating a higher energy component of the signal, and the correlation coefficient (ρ) is 0,746, showing a lower similarity between the original and reconstructed signals.

R_{xixj} shows values in the range of 0,688-0.702, which indicates a lower mutual correlation between different segments than was observed for Ensemble 1 (but also far from orthogonality) (Fig. 3).



Ensemble 1 Ensemble 2

Fig. 3 – Time decomposition of the first coarse level

Table 5 – Calculation of indicators of the average level of time decomposition

Ensemble 1					
Segment	MSE	SNR (dB)	Energy E	Correlation coefficient (ρ)	R_{xixj}
1	0,0251	15,122	10,11	0,972	0,935
2	0,0260	15,059	10,21	0,969	0,938
3	0,0246	15,251	9,87	0,974	0,942
4	0,0253	15,184	10,13	0,972	0,939
5	0,0262	15,030	10,30	0,968	0,936
6	0,0250	15,138	10,09	0,972	0,937
7	0,0249	15,161	10,06	0,973	0,941
8	0,0255	15,116	10,19	0,971	0,938
9	0,0247	15,209	9,89	0,973	0,940
10	0,0254	15,148	10,14	0,971	0,937
Ensemble 2					
Segment	MSE	SNR (dB)	Energy E	Correlation coefficient (ρ)	R_{xixj}
1	0,0762	11,435	40,12	0,906	0,812
2	0,0748	11,509	39,95	0,911	0,817
3	0,0774	11,370	40,50	0,903	0,808
4	0,0753	11,459	40,25	0,908	0,813
5	0,0739	11,553	39,78	0,912	0,819
6	0,0760	11,444	40,07	0,907	0,814
7	0,0745	11,479	39,89	0,910	0,815
8	0,0751	11,452	40,13	0,908	0,813
9	0,0736	11,575	39,68	0,913	0,820
10	0,0749	11,487	40,00	0,910	0,815

At the intermediate level, for Ensemble 1, MSE decreased by 75,5%, and SNR increased by 53,4%. The energy E decreased to 10,14, indicating more precise extraction of the medium-frequency components of the signal but also a loss of some useful signal. The correlation coefficient (ρ) increased from 0,887 to 0,971, indicating improved signal recovery accuracy but also an increase in mutual correlation, which is a drawback. For Ensemble 2, the average MSE decreased by 50,5%, and SNR increased by 38,2%. The correlation coefficient (ρ) rose to 0,910, indicating improved signal recovery accuracy, but it may also lead to signal overlap. The balance between the increase in ensemble signal volumes and mutual correlation is maintained.

At the fine level of time decomposition, the signal is further divided into smaller segments (Table 6).

Table 6 – Calculation of indicators for the fine level of time decomposition

Ensemble 1					
Segment	MSE	SNR (dB)	E	ρ	R_{xixj}
1	0,0052	20,346	2,01	0,991	0,967
2	0,0055	20,290	2,08	0,990	0,968
3	0,0051	20,404	1,98	0,992	0,970
4	0,0053	20,316	2,05	0,991	0,969
5	0,0054	20,301	2,06	0,991	0,967
...	...	...	...	...	...
50	0,0053	20,312	2,04	0,991	0,968
Ensemble 2					
Segment	MSE	SNR (dB)	E	ρ	R_{xixj}
1	0,0212	13,056	8,52	0,952	0,870
2	0,0209	13,110	8,48	0,953	0,872
3	0,0214	13,025	8,57	0,951	0,868
4	0,0211	13,073	8,50	0,953	0,871

5	0,0208	13,135	8,46	0,954	0,873
...	...	...	...	...	...
50	0,0210	13,097	8,49	0,953	0,870

In fig. 4 shows the comparative characteristics of Ensembles 1 and 2.

For Ensemble 1, the average MSE value at the coarse level was 0,1011. At the intermediate level, this value decreased to 0,0253, a 75,1% reduction. This indicates a significant reduction in signal reconstruction errors due to detailed analysis and extraction of the signal's mid-frequency components. At the fine level, the average MSE value decreased further to 0,0102, a 59,7% reduction compared to the intermediate level. Such optimization indicates even more accurate extraction of high-frequency components and further reduction of errors in signal reconstruction. The overall efficiency of the MSE metric from the coarse to the fine level was 89,9%, indicating the high effectiveness of the multiscale time decomposition method in reducing signal reconstruction errors, considering the features of Ensemble 1 components, such as low-frequency and mid-frequency sinusoidal signals, high-frequency noise, and impulses.

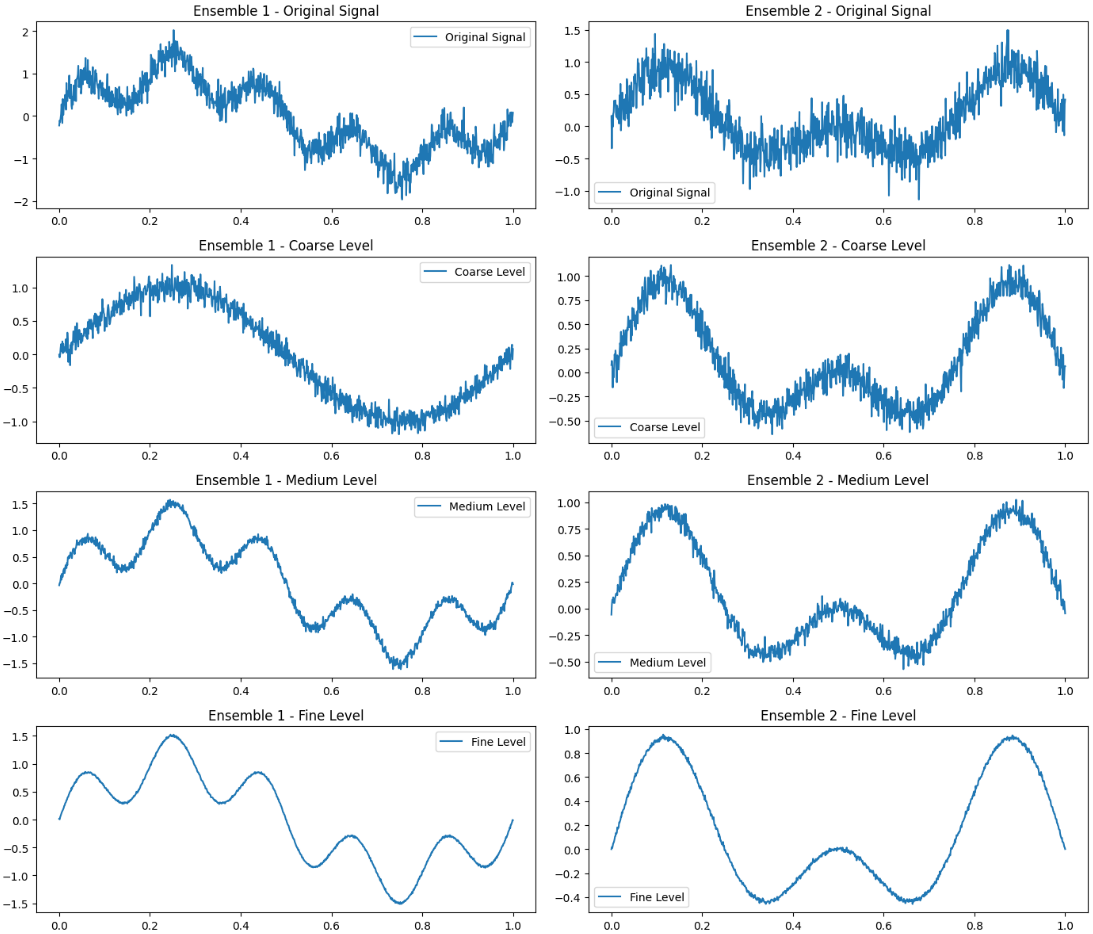


Fig. 4 – Optimization in the time domain on three levels

At the coarse level, the average SNR value for Ensemble 1 was 9,845 dB. At the intermediate level, this value increased to 15,150 dB, a 53,9% improvement, indicating a significant reduction in noise and improvement in signal reproduction. At the fine level, SNR increased to 20,150 dB, providing an additional optimization of 33,0% compared to the intermediate level. The overall improvement in the SNR metric from the coarse to the fine level is 104,6%, confirming the method's effectiveness in enhancing the signal-to-noise ratio.

The signal energy (E) is an indicator of signal stability. For Ensemble 1, the average energy value at the coarse level was 40,45. At the intermediate level, this value decreased to 10,11, indicating more accurate extraction of the signal's mid-frequency components and a reduction in noise impact. At the fine level, the average energy value further decreased to 5,15, confirming the method's effectiveness in extracting high-frequency components and reducing energy costs for signal processing.

The cross-correlation function (CCF) allows evaluating how well the reconstructed signal matches the original one at different time shifts, which is important for assessing delays and consistency between signals. For Ensemble 1, the CCF value at the coarse level was 0,800, at the intermediate level, it increased to 0,938, and at the fine level, it reached 0,951. These are fairly high values of cross-correlation between signals, but as noted above, this can occur when the volume of signal ensembles increases.

A comparison between Ensembles 1 and 2 shows that Ensemble 1's metrics were better optimized at each level of decomposition. This is due to the fact that Ensemble 1 contains less complex signals with a lower noise level.

Conclusions and prospects for further research.

This article proposed a three-level multiscale time decomposition method. The practical implementation of the algorithm for the proposed method substantiated the feasibility of its use for the analysis and processing of complex signals. Through detailed analysis and extraction of signal components at different levels of temporal detail, including coarse, medium, and fine levels, significant improvements in signal reconstruction accuracy were achieved.

Ensembles of complex signals obtained by time decomposition are advisable to use in conditions of high immunity, a large number of subscribers in cognitive radio networks, as well as in conditions of a high level of noise and interference. The use of this method helps to increase the productivity of the telecommunications system due to the optimization of the signal processing process and the reduction of computing costs.

Prospects for further research are the integration of the method with machine learning algorithms for automatic adaptation of decomposition parameters in real time, which will provide even greater efficiency and adaptability in the conditions of changing characteristics of the wireless cognitive telecommunication environment.

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