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REVUNOVA E.G.[1], DSc (Engineering),
Leading Researcher, Department of Neural Information Processing Technologies
https://orcid.org/0000-0002-3053-7090, e-mail: egrevunova@gmail.com
DESIATERYK O.O.[1, 2], PhD,
Assistant[1], Chair of Algebra and Computer Mathematics; Senior Researcherof the Department of Digital Systems for Ecological Monitoring, dept. 115.
https://orcid.org/0000-0002-7591-3846, e-mail: sasha.desyaterik@gmail.com
[1] International Research and Training Center for Information Technologies and Systems of the National Academy of Sciences of Ukraine and the Ministry of Education and Science of Ukraine,
40, Acad. Glushkov av., Kyiv, 03187, Ukraine
[2] Taras Shevchenko University of Kyiv, Faculty of Mechanics and Mathematics
4 e, Acad. Glushkov av., Kyiv, 03127, Ukraine

INFORMATION TECHNOLOGY OF JAMMING CANCELLATION

Introduction. *Impact of the jamming leads to the high losses since it decreases effectiveness of radiolocation systems, anti-aircraft missile systems and communication systems. Strategies of forming and setting of the jamming are improving and the power of the jamming increases. In this regard, it is important to improve jamming cancellation systems.*

The task of the improvement for based on matrix calculations methods of the jamming cancellation is actual considering the breakthrough development of the computational methods which allows realization by digital circuit engineering. These include the most modern machine learning algorithms aimed at solving signal processing tasks.

The requirement of the stable operation is important for the jamming cancellation systems under conditions of uncertainty. Other demand is an operation in the real time and a simple hardware implementation.

The purpose of the paper *is to increase the efficiency of the jamming cancellation in the antenna system (under conditions of uncertainty) based on the new randomized computation methods and their realization by the matrix-processor architecture.*

Results. *The approach based on singular value decomposition and random projection is proposed. It provides effective jamming cancellation in the antenna systems under conditions of uncertainty that is, the sample has small length, there is an own noise of the measuring system, the input-output transformation matrix have undefined numerical rank and there is no prior information about useful signal.*

Communication*. The increase of the efficiency of the jamming cancellation includes the increase of the stability and jamming cancellation coefficient, and the reduction of the computational complexity.*

The increase of the jamming cancellation coefficient is provided by use of stable discrete ill-posed inverse problems solution methods of the signal recovery based on random projection and singular value decomposition. The decrease of the computational complexity is achieved by the realization of random projection and singular value decomposition as the processor array which makes parallel computations.

Keywords: *information technology, jamming, machine learning, algorithms, singular value decomposition, random projection, conditions of uncertainty, signal recovery.*

INTRODUCTION

Nowadays the development of systems for the resistance to the electronic warfare equipment is obviously needed. Jamming usually created to decrease efficiency of radar systems, anti-aircraft missile systems, communication systems and so it leads to large losses. The power of jamming is increasing and strategies for forming (generating) and deploying jamming are being improved. Therefore, it is urgent to improve jamming cancellation systems.

On the other hand, in the counter electronic warfare systems the task of forming the directional pattern of the antenna system is relevant. The jamming cancellation is realized by appropriately beamforming the directional pattern in the direction of the jamming source [1–4].

The task of improving approaches, methods and algorithms of a beamforming for the antenna system based on matrix computations (decompositions) is relevant both in connection with the improvement of the digital element base and the breakthrough development of computational methods, which ensures implementation by means of digital circuitry. These include the most advanced neural network and machine learning algorithms aimed at solving signal processing problems.

At the same time, an important requirement is the requirement of stable work under conditions of uncertainty, that is, in the case of: a small sample length, the presence of self noise of the measuring system, an uncertain numerical rank of the input-output transformation matrix, and the absence of a priori information about the useful signal.

We also note the requirements for real-time operation and simple hardware implementation of the methods.

The aim of the work is to increase the efficiency of jamming cancellation in the antenna system (under conditions of uncertainty) based on new methods of randomization of computations and their implementation using a matrix-processor architecture.

INFORMATION TECHNOLOGY OF JAMMING CANCELLATION

The flowchart of the information technology of jamming cancellation is presented at Fig. 1.

Data for the information technology arrives both from measuring tools (presented by output of the measuring system) and from the corresponding generative models.

Data generated by model are the matrix $\mathbf{A}$ and measurement (output) vector.

Let us say a few words about properties of the matrix $\mathbf{A}$.

The transformation of the object signal when interacting with the propagation medium and the measuring system is modeled by a linear input-output transformation matrix.

In the case where the transformation matrix has a high conditional number, the sequence of its singular numbers falls to zero, and the output of the measuring system contains noise, the problem of estimating the input vector is called discrete ill-posed problem (DIP) [5, 6].

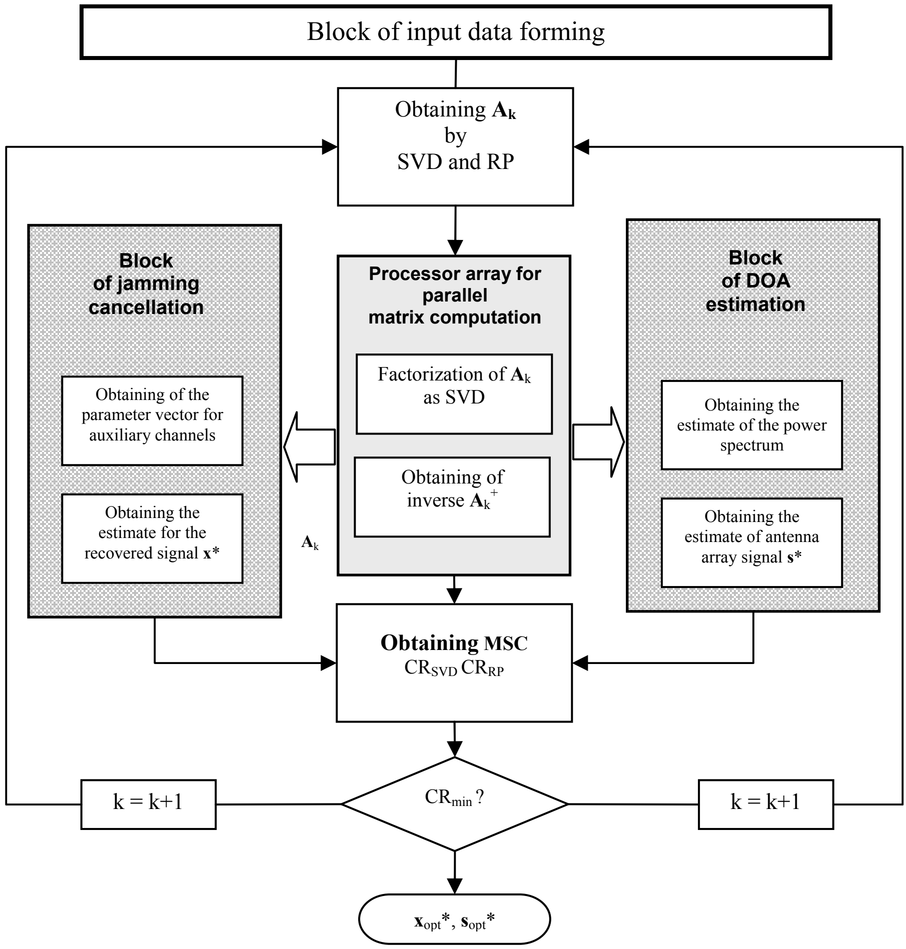


Fig. 1. Flowchart of the information technology of jamming cancellation

It is known that the DIP solution using pseudoinverse of the input-output transformation matrix is unstable. Small changes in the measurement (output) vector lead to large changes in the solution vector, while the value of the solution error is large.

To overcome the instability and, accordingly, to improve the accuracy of the solution, regularization methods are used. To overcome the instability and increase the accuracy of the DIP solution, one could use an approach based on Truncated Singular Value Decomposition (TSVD) [5, 6], and an approach using random projection [7–9].

In this article, the jamming cancellation problem and the problem of estimating the direction of arrival (DOA) of signals in an antenna system is considered as a DIP.

Model generated data is put to the matrix approximation block.

The input data matrix $\mathbf{A}$ is approximated by *k*-component model. In this block matrix $\mathbf{A}$ approximation by singular value decomposition and random projection is computed. The output of the matrix approximation block is a matrix $\mathbf{A}_k$.

The input matrix $\mathbf{A}$ is put to the block of parallel matrix computation in the processor array. This block conducts parallel computation of singular value decomposition for the data matrix in the array of elementary matrix processors [10–12]. In the process of iterative parallel computations the block finds singular value decomposition of the matrix $\mathbf{A}$, thus it forms $\mathbf{A}_k^*$ and $\mathbf{A}_k^+$.

Matrices $\mathbf{A}_k^*$ and $\mathbf{A}_k^+$ are inputs for the block of jamming cancellation and for the block which determines a direction of arrival of the signal.

The block of jamming cancellation computes the parameters vector of auxiliary channels and the estimation of the recovered signal.

The block which determines direction of arrival for signal computes the estimate of the antenna array output signal, power spectrum estimation and the direction of arrival of signal.

The recovered signal estimation **x*** and the output of antenna array signal estimation **s*** is forming at correspondent blocks by the *k*-component model.

The next step of data processing performs a block of computation of criteria CR(k) of model selection which preserves array of values from CR(1) to CR(k). Then the decision-making block on reaching the criteria minimum determines at which number of model components (k_{opt}) the value of criterion was minimal.

If the value CR(k) is not optimal then the value of k increases by one and the work of information technology continues.

If the value CR(k) is optimal then the information technology output consists of computed using the k_{opt} — component model:

– recovered denoised signal from the block of *jamming cancellation* and

– the estimation of antenna array output signal **s***, power specter and direction of arrival from the block which determines the *direction of arrival* for the signal.

EXAMPLES OF INFORMATION TECHNOLOGY WORK

Jamming cancellation modelling. For signals of auxiliary (compensation) channels the next model is used $\mathsf{X} = \mathsf{ZA} + \Theta$, where $\mathbf{X} \in \mathrm{C}^{L\times N}$ is a matrix of auxiliary channels signals; L is a number of samples; N is a number of auxiliary channels; $\mathbf{Z} \in \mathrm{C}^{L\times N}$ is a matrix of jamming signals; $\Theta \in \mathbf{C}^{L\times N}$ is a matrix of auxiliary channels self noise. Elements of Θ are random variables with normal distribution and zero mean. Jamming signals are commonly modeled by centered random variables with normal distribution.

Considering the model of signal forming for auxiliary channels the denoised signal (output of jamming cancellation algorithm) can be obtained as a residual of the main channel signal $\mathbf{y}$ and approximation of it by auxiliary channels signals. Thus $\mathbf{r} = \mathbf{y} - \mathbf{X}\mathbf{w}^*$, where $\mathbf{w}^* \in \Re^N$ is a weights vector such that signals of auxiliary channels are included to the main channel with these weights. The weights vector can be obtained directly by the truncated SVD as follows $\mathbf{w}^*_{k\ \text{SVD}} = \sum_{i=1}^{k} \mathbf{v}_i s_i^{-1} \mathbf{u}_i^{\mathrm{T}} \mathbf{y}$ and also by the random projection method $\mathbf{w}^*_{k\ \text{RP}} = (\mathbf{R}_k \mathbf{X})^+ \mathbf{R}_k \mathbf{y}$. The weights vector for the random projection method can be obtained by the singular value decomposition of the matrix $\mathbf{R}_k\mathbf{X}$. Thus, using $\mathbf{R}_k\mathbf{X} = \mathbf{U}_r\mathbf{S}_r\mathbf{V}_r^{\mathrm{T}}$ we obtain an inverse matrix $(\mathbf{R}_k\mathbf{X})^{+} = \mathbf{V}_r\mathbf{S}_r^{-1}\mathbf{U}_r^{\mathrm{T}}$ and the estimation of the weights vector $\mathbf{w}^{*}_{k\ \mathrm{RP}} = \mathbf{V}_r\mathbf{S}_r^{-1}\mathbf{U}_r^{\mathrm{T}}\mathbf{R}_k\mathbf{y}$.

The goal of the experimental study for different methods of jamming cancellation (based on *LMS*, *SVD*, *TSVD* and *TSVDs*) is to compare the behavior of the dependence of the cancellation coefficient (CC) from the level of its own noise and from the level of jamming (LJ) in conditions where the input matrix $\mathbf{X}$ close to rank deficient.

If the mixing matrix $\mathbf{A}$ contains linear dependent columns, then the matrix $\mathbf{X}$ is rank deficient.

The presence of self noise in the channels of the antenna system disturb the input matrix and make it a full rank (not rank deficient) matrix, but the condition number remains large.

The presence of self noise in additional channels is modeled by adding realizations of a random variable with a normal distribution.

Let us consider a case with $N = 4$ additional channels and a sample length $L = 10^3$. The useful signal is represented by a rectangular impulse with duration of 5 samples.

The amplitude of the useful signal in the experimental study was chosen so as not to exceed the level of jamming in the main antenna channel.

Experiment 1. Let us consider the dependence of the cancellation coefficient on the level of jamming. With increasing of LJ from 9.0×10^3 to 1.6×10^7 and self noise level 0.01 for *TSVDs* and *TSVD* methods CC is constant and equal respectively 9.19 and 9.195. In these conditions CC for *LMS* and *SVD* decrease from 8.7 to zero (Fig. 2, Tabl. 1).

The developed *TSVD* and *TSVDs* methods provide a stable high cancellation coefficient in the case of an increase of the level of jamming. For traditional *LMS*, *SVD* methods (based on LS), with an increase of the level of jamming from 2.0E+06 to 2.0E+07, the cancelling coefficient becomes less than one.

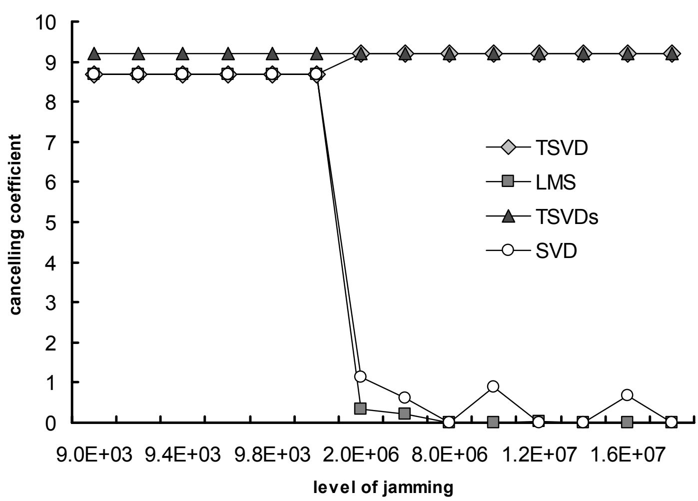


Fig. 2. Dependence of the cancelling coefficient on the level of jamming

Table 1. Dependence of the cancelling coefficient on the level of jamming

LJ	cancelling coefficient			
	TSVD	LMS	**TSVDs**	SVD
9.0E+03	8.686	8.686	9.195	8.686
9.4E+03	8.686	8.686	9.196	8.686
9.8E+03	8.686	8.686	9.194	8.686
2.0E+06	9.195	0.347	9.195	1.132
8.0E+06	9.195	0.004	9.195	0
1.2E+07	9.195	0.030	9.195	0
1.6E+07	9.195	0.002	9.195	0.668
2.0E+07	9.195	0.004	9.195	0

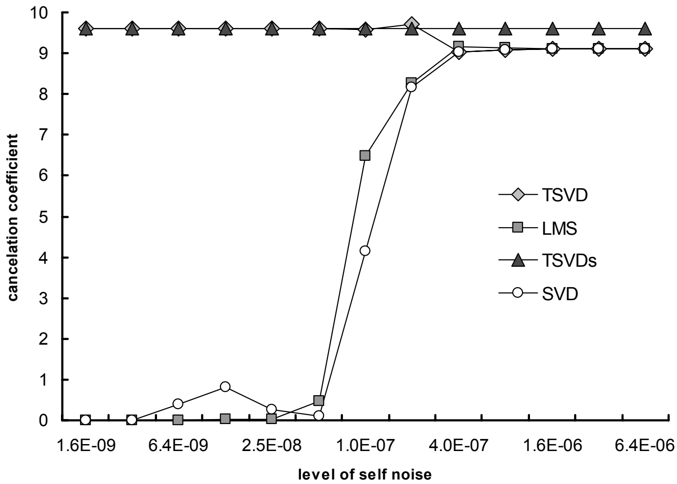


Fig. 3. Dependence of the cancellation coefficient on the level of self noise

The dependence of the CC on the LJ for the case when the matrix **A** is rank deficient. LJ varied in the range: 9.0×10^3, 9.2×10^3,...,1.2×10^7 is shown (Fig. 2). The level of self noise in additional channels is 0.1. As the LJ increases above 10^4, the CC values for *LMS* and *SVD* decrease. For the *TSVD* and *TSVDs* methods they are high, constant, and close to each other.

As the level of jamming increases compare with the level of self noise of the antenna channels, the matrix $\mathbf{X}$ becomes closer to rank deficient, since a small level of self noise no longer makes significant differences in the linearly dependent columns of the matrix $\mathbf{X}$. As a result, the instability of jamming cancellation methods based on matrix inversion, which assume that the matrix has full rank, such as *LMS* and *SVD*.

Experiment 2. Purpose of the experiment: for different methods of jamming cancellation (*LMS*, *SVD*, *TSVD*, *TSVDs*) compare the behavior of the dependence of the jamming cancellation coefficient on the level of the self noise of the additional channels in conditions close to the rank deficiency of the matrix of signals of the additional channels $\mathbf{X}$. The closeness of the matrix to the rank deficient is regulated by changing the level of self noise of the antenna channels at a fixed level of jamming. The lower the intrinsic noise level, closer the matrix $\mathbf{X}$ to the rank deficient.

In the range of channel self noise $1.6\times10^{-9},...,2.5\times10^{-8}$ with the jamming level of five, the TSVDs method provides a CC = 9.6. At the same time, for LMS and SVD, we observe CC values <1, this corresponds to jamming increase (Fig. 3).

The developed TSVD and TSVDs methods provide a stable high cancellation coefficient throughout the entire investigated range of self noise (Table 2). Traditional LMS, SVD methods for self-noise with level $1.6\times10^{-9},...,2.5\times10^{-8}$ give a cancellation coefficient less than 1.

Imitational modeling for DOA estimation. Let us consider a model of antenna array output forming. We model an output of antenna array under an assumption that sources are distant and narrowband. Under the assumption of a distant source the wave on the array of receivers is flat and moving from the source to the origin.

Output vector of the antenna array with K elements in a case of receiving M flat waves we present as follows: $\mathbf{y}(t)=\mathbf{A}(u)\mathbf{x}(t)+\mathbf{e}(t)$, where $\mathbf{A}(\theta)$ is a $K\times M$ matrix formed by direction vectors of antenna array $\{\mathbf{a}(\theta_i)\}$, $i=1,\ldots,M$, $\mathbf{x}(t)$ vector of sources signals (dimensionality M), $\mathbf{e}(t)$ is a K element noise vector, t is a time. The vector $\mathbf{y}$ obtained in a certain moment of the time we further call a sample. Number of all samples obtained in the time T we denoted by N.

Elements of the vector $\mathbf{a}(\theta_i)$ are defined by phase increments of the i-th signal (signal obtained from the i-th direction) to the corresponding antenna element:

$$\mathrm{a}(\theta_i)=[e^{-j\frac{2\pi}{\lambda}d_1 \sin(\theta_i)}, e^{-j\frac{2\pi}{\lambda}d_2 \sin(\theta_i)}, \ldots, e^{-j\frac{2\pi}{\lambda}d_K \sin(\theta_i)}]^{\mathrm{T}},$$

where λ is a wave length, d is a distance between antenna elements.

Let us consider results of the imitational modeling for determining of DOA by truncated singular value decomposition (TSVD), random projection (RP) and by method MUSIC.

Table 2. Dependence of the suppression coefficient on the level of inherent noise

SNL	suppression coefficient			
	TSVD	LMS	**TSVDs**	SVD
1.60E-09	9.604823687	0.004795	9.604824	0
6.40E-09	9.604823685	0.000747	9.604823	0.395168
2.50E-08	9.604823675	0.021755	9.604824	0.25396
1.00E-07	9.572287004	6.488008	9.604826	4.142304
4.00E-07	9.039153315	9.1575	9.604823	9.039153
1.60E-06	9.111092835	9.11971	9.604706	9.111093
6.40E-06	9.11860288	9.118267	9.604693	9.118603
2.56E-05	9.118208783	9.1182	9.603538	9.118209

By the analysis from the previous work follows that advantages of methods TSVD and RP (as parametric methods) compared to non-parametric MUSIC the most obviously appear in the case of small number of samples and also when sources signals are correlated. The experimental study should confirm the conclusions of the best work of TSVD and RP.

Imitational modeling was made for the case of two signal sources with angle coordinates 10 and 20 degrees at signal-to-noise ratio SNR = 0.

Dependencies $P(\theta)$ were studied in conditions of correlated sources and a small number of samples. Source correlation was modeled by assigning the same frequencies to the signal sources.

We studied the dependency of power from the angle ($P(\theta)$) for N=100, $\omega_1 = \pi/4$, $\omega_2 = \pi/4$ when K=91 (fig. 4-a) and when K=45 (fig. 4-b). Modeling for RP and TSVD was made in real numbers.

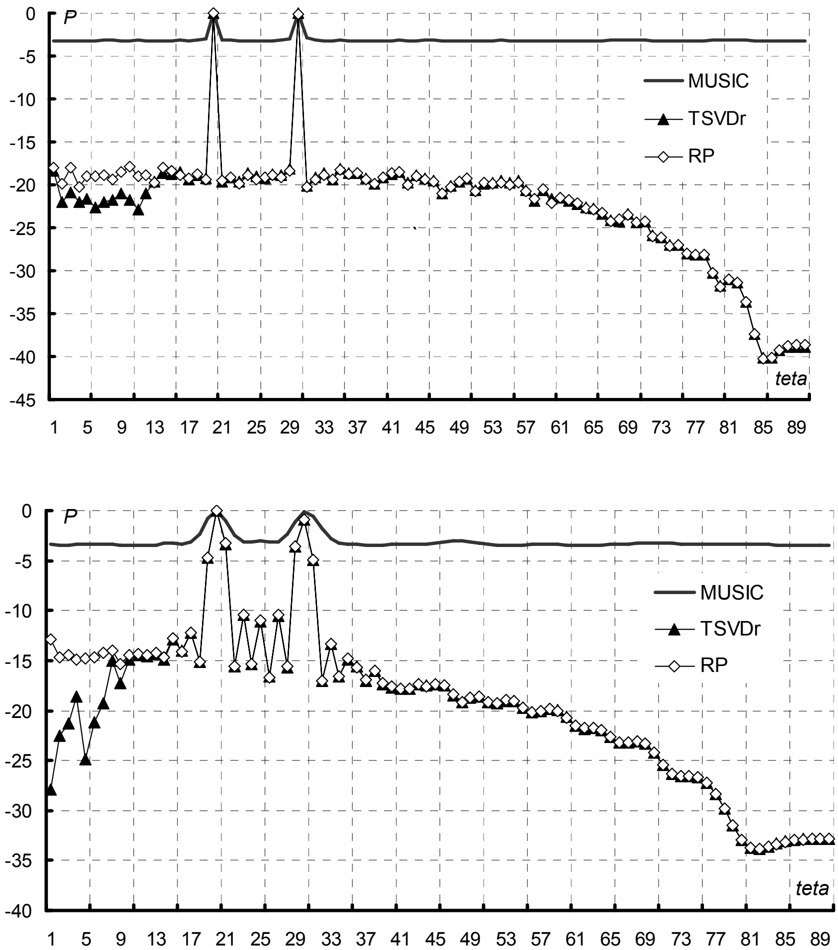


Fig. 4. The dependence of radiation power from the angle $P(\theta)$ for methods MUSIC, TSVD and RP for N = 100, K = {91, 45}

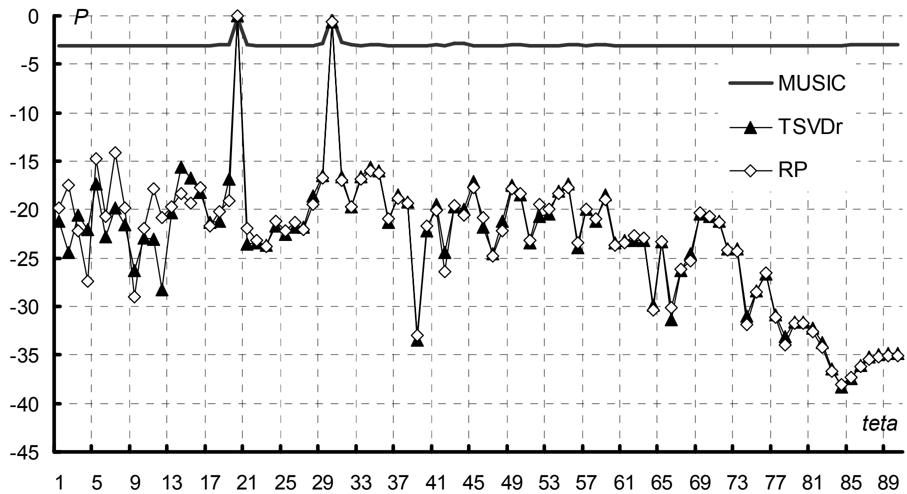
Method MUSIC works bad for both K=91 (level of $P(\theta)$ out of directions to the sources is –4 dB) and for K=45 (level of $P(\theta)$ out of directions to the sources is –3.5 dB). The TSVD and RP methods work much better than MUSIC.

For TSVD and RP the level of $P(\theta)$ out of directions to the sources does not exceed –18.5 dB when $K = 91$ and –10 dB when $K = 45$.

We also studied a dependency $P(\theta)$ for $N = 5$, $\omega_1 = \pi/4$, $\omega_2 = \pi/4$ when $K = 91$ (Fig. 5-a) and when $K = 45$ (Fig. 5-b).

Method MUSIC provides the out of directions to the sources $P(\theta)$ level –4 dB for K=91 and $P(\theta)$ at the level –3 dB for K=45. TSVD and RP methods work better then MUSIC.

For TSVD and RP the $P(\theta)$ level out of directions to the sources does not exceed –14 dB for $K = 91$ and –10 dB for $K = 45$.



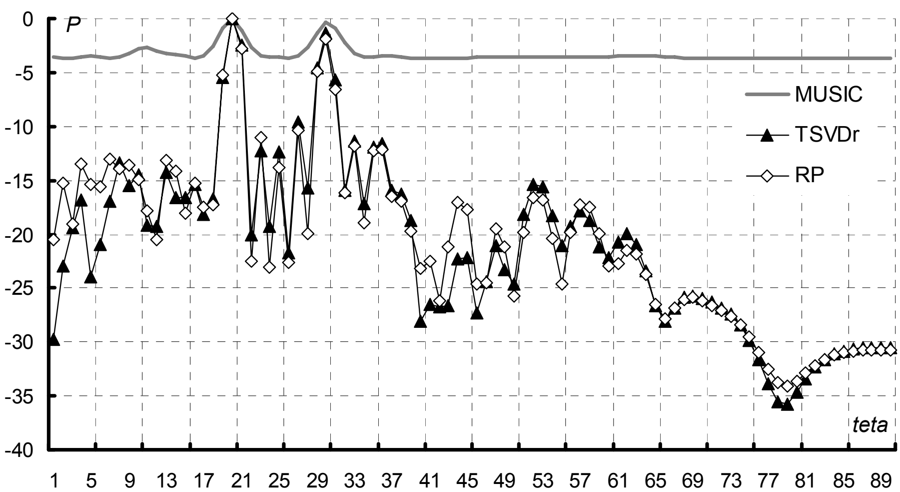


Fig. 5. The dependence of radiation power from the angle $P(\theta)$ for methods MUSIC, TSVD and RP for $N = 5$, $K = \{91, 45\}$

CONCLUSIONS

We make an experimental study of the efficiency for jamming cancellation and DOA methods realized by using matrix processor array (for parallel computations). Experimental study showed that the realization of developed TSVD and RP methods as a matrix processor array provides effective processing of signals from the antenna array.

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Ревунова О.Г.[1], д-р. техн. наук, старш. наук. співроб.,
провід. наук. співроб. відд. нейромережевих технологій оброблення інформації,
https://orcid.org/0000-0002-3053-7090, e-mail: egrevunova@gmail.com
Десятерик О.О.[1,2], канд. фіз.-мат. наук,
асистент кафедри алгебри і комп'ютерної математики[1], старший наук[2]. спів роб. відд. 115
https://orcid.org/0000-0002-7591-3846, e-mail: sasha.desyaterik@gmail.com
[1] Міжнародний науково-навчальний центр інформаційних технологій
та систем НАН України та МОН України,
пр. Акад. Глушкова 40, м. Київ, 03187, Україна
[2] Київський національний університет імені Тараса Шевченка
пр. Акад. Глушкова 4є, м. Київ, 03127, Україна

ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ ПРИГНІЧЕННЯ АКТИВНИХ ЗАВАД

Вступ. *Дія активної завади призводить до великих втрат через зниження ефективності роботи радіолокаційних систем, зенітно-ракетних комплексів, систем зв'язку. Удосконалюються стратегії формування та постановки активної завади, зростає потужність завади. Тому актуальним є вдосконалення систем пригнічення активних завад. Завдання удосконалення підходів та методів пригнічення активних завад на основі матричних обчислень є актуальним у зв'язку з проривним розвитком обчислювальних методів, що допускають реалізацію засобами цифрової схемотехніки. До них відносяться найсучасніші алгоритми машинного навчання, спрямовані на вирішення завдань обробки сигналів. Важливою є вимога сталої роботи систем пригнічення активних завад за умов невизначеності. Також вимогою є робота в реальному часі та проста апаратна реалізованість методів.*

Метою *роботи є підвищення ефективності пригнічення активних завад в антенній системі (в умовах невизначеності) на основі нових методів рандомізації обчислень та їх реалізація за допомогою матрично-процесорної архітектури.*

Результати. *Запропоновано підхід (заснований на сингулярному розкладанні та випадковій проекції), що забезпечує ефективне пригнічення активних завад в антенній системі за умов невизначеності, тобто при: малій довжині вибірки, наявності власного шуму вимірювальної системи, невизначеному чисельному рангу матриці перетворення вхід-вихід, відсутності апріорної інформації про корисний сигнал.*

Обговорення. *Підвищення ефективності пригнічення завад включає: підвищення стійкості та коефіцієнта пригнічення завади, зниження обчислювальної складності. Підвищення коефіцієнта пригнічення завади забезпечується використанням стійких методів розв'язання дискретних некоректних обернених завдань відновлення сигналів на основі випадкової проекції та усіченого сингулярного розкладання. Зниження обчислювальної складності досягається за рахунок реалізації випадкової проекції та усіченого сингулярного розкладання процесорним масивом, що реалізує паралельні обчислення.*

Ключові слова: *активна завада, сингулярне розкладання, випадкова проєкція.*