THEORY AND METHODS OF SIGNAL PROCESSING

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SYNTHESIS OF NONPARAMETRIC ALGORITHMS FOR DETECTION OF RADAR CORRELATED SIGNALS AGAINST THE BACKGROUND OF MARKOV CORRELATED NOISE

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Abstract*—The article deals with the technology of construction of nonparametric processing methods of correlated random processes. The use of a Markov model of correlated signals allows to synthesize the nonparametric rank algorithms that use nonparametric estimation of a one-dimensional cumulative distribution function using a training sample containing interference only. The theory of synthesis of nonparametric rank Markov decision rules is constructed, the problem of synthesis of rank nonparametric algorithm for detection of correlated signal against the background of uncorrelated noise on the output of amplitude demodulator is solved. Property of this algorithm is investigated.*

Index Terms—Signal processing; robust rank algorithms; radar signal detection; Markov correlated noise; aproristick uncertainity.

I. INTRODUCTION

The onset of nonparametric detection theory was recorded in 1936 when Hoteling and Pabst published an article on rank correlation. Since then, a large number of papers on nonparametric methods of information processing have been published [1] – [17].

Although nonparametric or distribution-free methods have been studied and applied by statisticians for at least 50 years, only recently have engineers recognized their importance and begun to investigate their applications.

The widespread use of radar, navigation and communications in a variety of fields (aviation, medicine, vehicle management, etc.) puts a growing number of tasks at stake in improving their performance in complex applications [17] – [22].

Typically, radar is used in complex interference situations (terrain and type of background surface, various meteorological conditions, man-made and organized interferences, etc.). To work effectively under these conditions, the signal processing channels are equipped with several of signal detection means against the background of various interferences and evaluation of their informative parameters.

In the case of automatic control of the radar mode in the a priori uncertainty of the spatial location of the interferences and their statistical distributions, the radar itself and the obstacle analyzer are the object of control. The task of the radar control of the analyzer is to collect information about the surrounding operational-tactical situation and make a decision on the choice of the optimal radar mode. Moreover, the analyzer not only measures the characteristics of the interference but also classifies them. Noise is classified by correlation coefficient (correlated or uncorrelated). Correlation propertis of interference is detected and analyzed throughout the radar work area.

II. TASK STATEMENT

Currently, the problem of noise classification is solved by the method of estimating the correlation coefficient by the maximum likelihood estimation algorithm for the Gaussian noise distribution model. However, in most situations the assumption of Gaussianness does not meet the real conditions. Therefore, the signal distribution at the output of the amplitude detector is not Gaussian and is described, in the general case, by Rice's law. The effect of artificial or natural impulse noise causes the Gaussian model to be abandoned and nonparametric methods are resorted to.

All of the classic nonparametric detectors are based on the assumption that the input observations are independent and identically distributed. Since there are many radar situations which may give rise to correlation of input observations (earth reflections interference, sea clutter etc), is importen to consider a nonparametric approach to synthesis of signal detection algorithms for thees cases and to investigate their properties.

In this paper, we consider a nonparametric approach to the problem of detecting highly correlated radar reflections against a background of weakly correlated noise.

III. SYNTHESIS OF PARAMETRIC DECISION RULE ON A UNIT N-CUBE

Distribution-free procedures can solve a number of signal detection tasks during interference with a priori undefined characteristics. The main task of detecting signals in a nonparametric formulation can be formulated as a task of comparing two samples. The hypothesis H_0 under test is that two random samples $x_1, ..., x_n$ and $y_1, ..., y_m$ have the same probability distribution, that is, generated by the interference. No assumptions are made about the probability of interference, except for the continuity and independence of random values.

The presence of a signal may change the shift parameter, change the scale of one of the samples, produce a correlation of the sample $x_1, ..., x_n$, or change the distribution pattern of the sample $x_1, ..., x_n$ compared to the sample distribution $y_1, ..., y_m$.

The main requirement for nonparametric procedures is the statistical independence of the sample values $x_i, i=\overline{1,n};\ y_j, j=\overline{1,m}$. We show that nonparametric signal processing procedures can be constructed in the case of Markov correlated noise.

The distribution-free statistics are based on the fact that the random variable U obtained by transformation

$$u_i = F(\nu_i),\ i=\overline{1,n}, \tag{1}$$

where v_i are random values of the random variable V, $F(\cdot)$ is an cumulative distribution function of a random variable V, has uniform distribution over the interval [0,1]. Vector $u_1,...u_n$, the coordinates of which are obtained as a result of transformation (1), can be considered as an element of a unit n-dimensional cube.

Let $x_1, ..., x_n$ be a sample of stationary Markov noise of kth order

$$x_i = \sum_{j=1}^{\min\{i,k\}} a_j x_{i-j} + w_i,\ i=\overline{1,n}, \tag{2}$$

where $w_i,\ i=\overline{1,n}$ are the Gaussian white noise samples, $x_0 = 0$.

The Markov interference property allows us to present a multidimensional sample distribution density as the product of the unconditional $\phi(x_1)$ and conditional probability densities

$$\varphi_i(x_i \mid x_{i\text{-}1},..,x_{i\text{-j}}),\quad i=\overline{1,n};\ j=\min\{i,k\},$$

to which continuity conditions are imposed are the conditional densities of the process probability distributions at ith times.

$$\begin{aligned} f(x_1,..,x_n) = \phi(x_1)\varphi_2(x_2 \mid x_1)\varphi_3(x_3 \mid x_2, x_1) \\ ...\varphi_i(x_i \mid x_{i-1}, x_{i-2},.., x_{i-k}) \\ ...\varphi_n(x_n \mid x_{n-1}, x_{n-2},.., x_{n-k}), \end{aligned} \tag{3}$$

where $\varphi_2(*), \varphi_3(*),..,\varphi_k(*),\varphi_{k+1}(*)=\varphi_{k+2}(*)= ...=\varphi_n(*)$.

Let be an analytical kind of conditional $\varphi_i(x_i)$ and unconditional probability distribution densities

$$\phi(x_i) = \int_{x_{i\text{-}1}}.\int_{x_{i\text{-}j}} \varphi_i(x_i \mid x_{i\text{-}1},..., x_{i\text{-}j})dx_{i\text{-}1}...dx_{i\text{-}j},$$

$$i=\overline{2,n};\quad j=\min\{i,k\}$$

are know, and $F(x) = \int_{-\infty}^{x} \phi(t)dt$ is the accordingly, the unconditional cumulative distribution function.

We introduce nonlinear transformations

$$u_i = F(x_i),\ i=\overline{1,n}, \tag{4}$$

and find a multidimensional probability distribution of the sequence $u_1,..,u_n$.

Jacobian conversion

$$J = \begin{pmatrix} \dfrac{\partial x_1}{\partial u_1} & .... & \dfrac{\partial x_1}{\partial u_n} \\ .... & .... & .... \\ \dfrac{\partial x_n}{\partial u_1} & .... & \dfrac{\partial x_n}{\partial u_n} \end{pmatrix} = \left(\prod_{i=1}^{n} \phi\left(F^{-1}(u_i)\right)\right)^{-1},$$

where $F^{\text{-}1}(u_i),\ i=\overline{1,n}$ are transformations inverted to (4).

Then the multidimensional distribution density of the transformed variables will look like this

$$\begin{aligned} Q(u_1,..,u_n) &= f(F^{-1}(u_1),.., F^{-1}(u_n))J \\ &= \frac{\varphi_1(F^{-1}(u_1))}{\varphi_1(F^{-1}(u_1))}\cdot\frac{\varphi_2\left(F^{-1}(u_2) \mid F^{-1}(u_1)\right)}{\phi(F^{-1}(u_2))} \\ &\cdot ...\cdot \frac{\varphi_n\left(F^{-1}(u_n) \mid F^{-1}(u_{n-1}),.., F^{-1}(u_{n-k})\right)}{\phi(F^{-1}(u_n))}. \end{aligned} \tag{5}$$

Expression (5) can be represented in the form of product of factors

$$\begin{aligned} Q(u_1,..,u_n) &= \\ &= \prod_{i=2}^{n} \frac{\varphi_i\left(F^{-1}(u_i) \mid F^{-1}(u_{i-1}),.., F^{-1}(u_{n-\min\{i,k\}})\right)}{\phi\left(F^{-1}(u_i)\right)} \\ &= \prod_{i=2}^{n} C_i\ \left(u_i \mid u_{i-1},..u_{i-\min\{i,k\}}\right). \end{aligned} \tag{6}$$

That is, the multidimensional distribution of the k-connected Markov random variables normalized by the marginal cumulative functions (4), is the product of the factors

$$C_i(u_i \mid u_{i-1},...,u_{i-\min\{i,k\}}),\ i=\overline{2,n}.$$

The distribution (6) will be called Markov copula. Consider the problem of synthesis of a decisive rule on a unit n-dimensional cube.

Consider two hypotheses, $H_0: f(\bar{x})=f_0(\bar{x})$ and, $H_1: f(\bar{x})=f_1(\bar{x})$ and, $\phi_0(x)$, $\phi_1(x)$, $\varphi_{0i}(*)$ and $\varphi_{1i}(*)$, $i=\overline{2,n}$ are unconditional one-dimensional and conditional distributions for hypotheses H_0 and, H_1 respectively, for a sample $x_1,...,x_n$ of a Markov k-order random process given by (2). Then the decisive rule on the n-dimensional unit cube, by the Neumann–Pearson criterion, is determined by the relation of the likelihood functions (6)

$$\Lambda(\bar{u})=\log\frac{f_1(\bar{u})}{f_0(\bar{u})}=\log\frac{\prod_{i=1}^{n}\varphi_{1i}\left(F^{-1}(u_i)\mid F^{-1}(u_{i-1}),...,F^{-1}(u_{n-\min\{i,k\}})\right)\phi_0\left(F^{-1}(u_i)\right)}{\prod_{i=1}^{n}\varphi_{0i}\left(F^{-1}(u_i)\mid F^{-1}(u_{i-1}),...,F^{-1}(u_{n-\min\{i,k\}})\right)\phi_1\left(F^{-1}(u_i)\right)}>V(\alpha,n), \quad (7)$$

where α is the given probability of errors of the first kind.

The random variables $u_i, i=\overline{1,n}$ under the hypothesis H_0 are evenly distributed over the interval [0,1], regardless of the marginal probability distribution $\phi_0(x)$. Therefore, the decision threshold $V(\alpha,n)$ depends only on the given probability of an error of the first kind α (false alarm) and the sample size n.

III. Synthesis of Rank Nonparametric Signal Processing Procedures

In nonparametric problems, the integral noise distribution function F is unknown. Therefore, according to the empirical Bayesian approach, they try to obtain an estimate of the noise distribution function by using a training or reference sample $y_1,...,y_m$, which contains only the noise distribution $F^*(*)$, and use this estimate to construct a nonlinear transformation (1). Thus, the signal samples $x_1,...,x_n$ are transformed according to the algorithm

$$u_i=F^*(x_i),\ i=\overline{1,n}, \quad (8)$$

and hypothesis H_0 about the uniformity of distribution of random variable U is tested. If this hypothesis is accepted, then we conclude that hypothesis H_0 holds that samples x_1, ..., x_n and y_1,..., y_m belong to the same distribution, that is, sample x_1,..., x_m contains no signal. Otherwise, it is decided that the hypothesis H_1 holds, that is, the sample x_1,..., x_m contains the signal.

A. Synthesis of Nonparametric Post-Detector Correlated Signal Detection Algorithm Against Gaussian Uncorrelated Noise

Consider sampling the values of the envelope Gaussian noise at the output of the amplitude detector obtained with time-domain sampling $\Delta\tau$

$$x_1,...,x_n. \quad (9)$$

The one-dimensional density distribution of the Gaussian envelope noise is described by Rayleigh's law

$$\phi_0(x_i)=\frac{x_i}{\Psi}\exp\left(-\frac{x_i^2}{2\Psi}\right),\ x_i\geq 0,\ i=\overline{1,n}. \quad (10)$$

Appropriate cumulative probability distribution function

$$F(x_i)=1-\exp\left(-\frac{x_i^2}{2\Psi}\right),\ x_i\geq 0. \quad (11)$$

We assume that the process at the input of the detector is a narrow-band normal noise with a correlation function

$$B(\tau)=\Psi\exp(-\beta|\tau|)\cos(\omega_0\tau), \quad (12)$$

where Ψ is the noise dispersion; ω_0 is the center frequency; β is the parameter of the correlation function that characterizes the process frequency bandwidth.

This process is a white Gaussian noise that has passed through the oscillatory high-Q factor RLC circuit [23]. A envelope of process is a Markov process with a multidimensional PDF

$$f(\bar{x})=\phi_0(x_1)\prod_{i=2}^{n}\varphi_i(x_i\mid x_{i-1}),$$

where $\phi_0(x_1)$ defined by formula (10) and the transition probabilities

$$\varphi_i(x_i\mid x_{i-1})=\frac{x_i}{\Psi(1-r^2)}\exp\left(-\frac{r^2x_{i-1}^2+x_i^2}{2\Psi(1-r^2)}\right)\cdot I_0\left(\frac{rx_1x_2}{\Psi(1-r^2)}\right),\quad i=\overline{2,n},\ x_i>0, \quad (13)$$

where $I_0(*)$ is the modified Bessel function of the first kind for real positive argument; r is the value of the envelope of correlation function of a narrowband random process at the input of the detector

$$r = \exp(-\beta|\Delta\tau|).$$

Let the presence of a signal change the correlation properties of the sequence (9).

Two hypotheses are tested for this sample,

$$H_0 : f(\bar{x}) = f(\bar{x}, r = 0)$$

and

$$H_1 : f(\bar{x}) = f(\bar{x}, r = r_0 > 0).$$

The one-dimensional PDF of the envelope is independent of the correlation coefficient and by H_1 is also described by Rayleigh law

$$\phi_1(x_i) = \frac{x_i}{\Psi}\exp\left(-\frac{x_i^2}{2\Psi}\right), \quad x_i \geq 0, \quad i = \overline{1,n}. \quad (14)$$

The parametric algorithm for testing these hypotheses is obtained by substituting in (8) expressions (10), (11), (13) and (14), where the values r correspond to the two hypotheses being tested.

To synthesize a nonparametric algorithm, it is necessary to construct an estimate of the cumulative probability distribution function of the envelope for the situation when the signal is absent ($r = 0$) $F^*(x)$ and make the transformation $u_i = F^*(x_i)$, $i = \overline{1,n}$.

To do this, we need to obtain a sample of envelope uncorrelated noise $y_1,...,y_m$, construct a variational series and determine the rank of reference x_i in it

$$\text{rank}_i = \sum_j^m \text{sgn}(x_i - y_j),$$

$$\text{sgn}(z) = \begin{cases} 1, & z > 0, \\ 0, & z <= 0. \end{cases}$$

Next, we obtain the normalized values

$$u_i(x_i) = 1 - \frac{\text{rank}_i + 1}{m+2}, i = \overline{2,n}$$

and inverted to (11) (by $\Psi = 1$) transformed values

$$F^{-1}(\text{u}_i) = \sqrt{-2\ln(u_i)}, i = \overline{2,n}.$$

Substitute them for the likelihood functions ratio (7) we will get

$$\varphi_{1i}(u_i \mid u_{i\text{-}1}) = \frac{\sqrt{-2\ln(u_i)}}{(1-r^2)}\exp\left(-\frac{r^2\ln(u_{i-1}) + \ln(u_i)}{(1-r^2)}\right)I_0\left(\frac{2r\sqrt{\ln(u_{i-1})\ln(u_i)}}{(1-r^2)}\right), \ i = \overline{2,n}, \ u_i > 0, \ u_{i\text{-}1} > 0,$$

$$\phi_{0i}(u_i) = u_1\sqrt{-2\ln(u_i)}\exp\left(\ln(u_i)\right) = u_1\sqrt{-2\ln(u_i)}, \ i = \overline{1,n};$$

$$C_i\,(u_i \mid u_{i-1}) = \frac{\varphi_i(u_i \mid u_{i\text{-}1})}{\phi_0(u_i)} = \frac{1}{u_i(1-r^2)}\exp\left(-\frac{r^2\ln(u_i) + \ln(u_i)}{(1-r^2)}\right)I_0\left(\frac{2r\sqrt{\ln(u_{i-1})\ln(u_i)}}{(1-r^2)}\right), \quad (15)$$

$$i = \overline{2,n}, \ u_i > 0, \ u_{i\text{-}1} > 0,$$

We use the Bessel approximation for $r > 0$

$$I_0\left(\frac{2r\sqrt{\ln(u_{i-1})\ln(u_i)}}{(1-r^2)}\right) = \frac{\sqrt{(1-r^2)}}{\sqrt{4\pi r\sqrt{\ln(u_{i-1})\ln(u_i)}}}\exp\left(\frac{2r\sqrt{\ln(u_{i-1})\ln(u_i)}}{(1-r^2)}\right), \quad (16)$$

and get

$$C_i\,(u_i \mid u_{i-1}) = \frac{\sqrt{(1-r^2)}}{u_i\sqrt{4\pi r\sqrt{\log(u_{i-1})\log(u_i)}}}\exp\Big(-\frac{r^2\ln(u_i) + \ln(u_i) - 2r\sqrt{\ln(u_{i-1})\ln(u_i)}}{(1-r^2)}\Big), \quad (17)$$

$$i = \overline{2,n}, \ u_i > 0, \ u_{i\text{-}1} > 0,$$

The decisive rule for testing a hypothesis $H_1 : r = r_0 > 0$ is as follows

$$\Lambda(\bar{u}) = \sum_{i=1}^n \ln(C_i) = -\sum_{i=1}^n \frac{\left(r_0\sqrt{\ln(u_{i-1})} - \sqrt{\ln(u_i)}\right)^2}{(1-r_0^2)} - \ln(u_i) + \ln\sqrt{(1-r_0^2)} - \ln\left(\sqrt{4\pi r_0\sqrt{\ln(u_{i-1})\ln(u_i)}}\right). \quad (18)$$

B. Performance Analysis

Performance analysis was performed using the Monte Carlo method.

We model the Markov sequence of values of the enveloping Gaussian correlated process as the square root of the sum of two correlated quadratures

$$x_{i+1} = \sqrt{y_i^{\,2} + (z_i + \varsigma_i)^2}\,,\ i = \overline{1,n}. \qquad (19)$$

Quadrature components are Markov sequences that are formed by a rule

$$y_{i+1} = ry_i + \sqrt{(1-r^2)}\eta_i,\ i = \overline{1,n};$$
$$z_{i+1} = rz_i + \sqrt{(1-r^2)}w_i,\ i = \overline{1,n},$$

where η_i, w_i, $i = \overline{1,n}$ are samples of uncorrelated normalized Gaussian noise; r is the correlation coefficient in quadratures; ς_i, $i = \overline{1,n}$ are samples of haotick clutter, that have the following probability distribution

$$f(\varsigma) = (1-p)\delta(\varsigma) + p\lambda\exp(-\lambda\varsigma),\ p \in [0,1]. \qquad (20)$$

The correlation coefficient of adjacent envelope values by $p = 0$ is calculated by the formula [23]

$$R = \frac{\pi}{4(4-\pi)} r^2.$$

The first value of sequence (19) is distributed by Rayleigh law and can be obtained according to the formula

$$x_1 = \sqrt{-2\Psi \ln(\upsilon)},$$

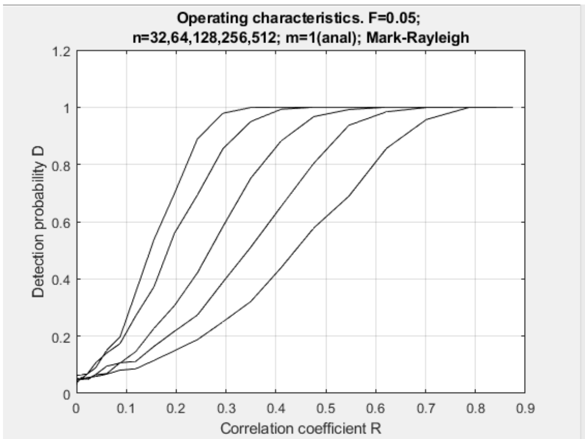
where υ is a random variable with uniform distribution over the interval [0,1].

To estimate the detection probability, N correlated sequences were formed, according to rule (19), with a given correlation coefficient, validation statistics were calculated (18), compared with the decision threshold V, and the number of positive decisions was calculated – m. The estimate of the probability of detecting the correlation of a Markov sequence with the correlation coefficient r is given by the relation $D = m / N$.

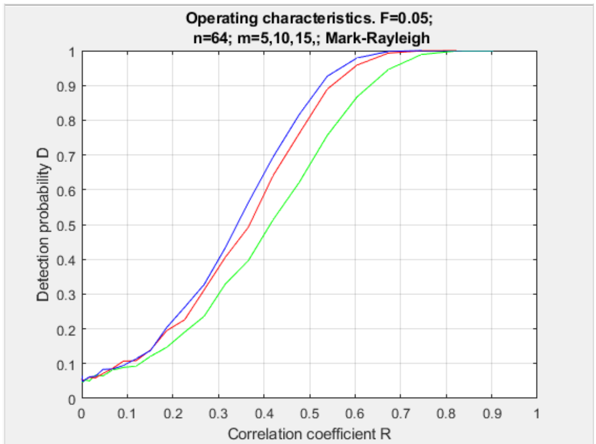
The decision threshold V was calculated as a quantile of the 0.95 distribution of validation statistics (18) at $r = 0$.

Figure 1 shows the detection characteristics of algorithm (18), calculated for different values in the number of tests $N = 1000$.

On the Figure 2 one can see influence of pulse clutter on operating characteristics both rank and MP algorithms. Rank algorithm is more robust to pulse clutter.



(a)



(b)

Fig. 1. Nonparametric algorithm detection characteristics (18) without pulse clutter ($p = 0$): (a) is the different size of signal sampling ($n = 32, 64, 128, 256$), volume of training sample $m = 20$; (b) is the signal sampling size $n = 64$, different training sample size ($m = 5, 15, 20$)

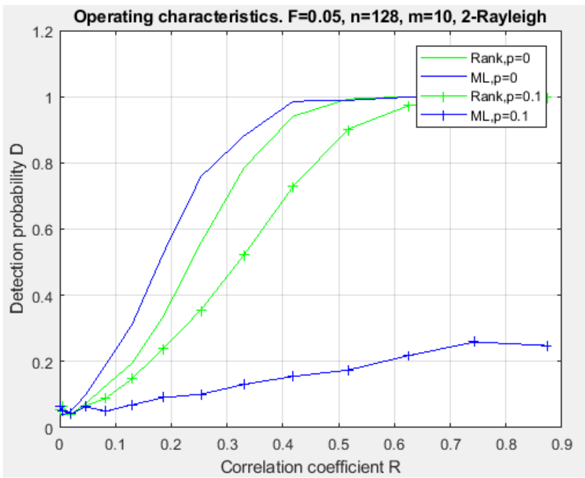


Fig. 2. Nonparametric algorithm detection characteristics (18), markt “Rank”, and algorithm, used maximum likelyhood estimation of correlation coefficient, markt “ML”, without pulse clutter ($p = 0$) and) with pulse clutter ($p = 0.1$)

IV. CONCLUSIONS

The proposed theory allows to synthesize effective nonparametric algorithms for signal processing under the influence of Markov correlated noise, which use nonlinear transformation of sample values according to the estimation of one-dimensional cumulative probability distribution function over the variational series of training sample of noise.

The example of synthesis of the algorithm for detecting correlated random signal at the output of a linear Gaussian noise detector is demonstrated. It demonstrates the feasibility of the proposed approach to the synthesis of nonparametric signal processing algorithms.

The results of the analysis of the influence of the size of the training sample on the efficiency of the algorithm show that even at 15 noise samples used to construct the variational series of interference, potential efficiency is practically achieved (Fig. 1).

Investigation of robustness shows (Fig. 2): synthesized rank algorithm is more robust then the parametrical ML algorithm.

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І. Г. Прокопенко. Синтез непараметричних алгоритмів для виявлення радіолокаційних корельованих сигналів на тлі марковского корельованого шуму

У статті розглянуто технологію побудови непараметричних методів обробки корельованих випадкових процесів. Використання марковської моделі корельованих сигналів дозволяє синтезувати непараметричні рангові алгоритми, які використовують непараметричну оцінку одновимірної інтегральної функції розподілу з використанням навчальної вибірки, що містить лише заваду. Побудовано теорію синтезу непараметричних рангових марковських вирішувальних правил, вирішено задачу синтезу рангового непараметричного алгоритму виявлення корельованого сигналу на тлі некорельованого шуму на виході амплітудного демодулятора. Досліджено ефективність і робастність цього алгоритму.

Ключові слова: обробка сигналу; робастні алгоритми рангу; виявлення радіолокаційного сигналу; марковський корельований шум; апріорна невизначеність.

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И. Г. Прокопенко. Синтез непараметрических алгоритмов для обнаружения радарных коррелированных сигналов на фоне марковского коррелированного шума

В статье рассмотрены технологии построения непараметрических методов обработки коррелированных случайных процессов. Использование марковской модели коррелированных сигналов позволяет синтезировать непараметрические ранговые алгоритмы, в которых используется непараметрическая оценка одномерной интегральной функции распределения с использованием обучающей выборки, содержащей только помеху. Построена теория синтеза непараметрического рангового марковского правила принятия решений, решена задача синтеза рангового непараметрического алгоритма обнаружения коррелированного сигнала на фоне некоррелированного шума на выходе амплитудного демодулятора. Исследованы эффективность и робастность этого алгоритма.

Ключевые слова: обработка сигнала; робастные ранговые алгоритмы; обнаружение радиолокационного сигнала; марковский коррелированный шум; априорная неопределенность.

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