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Robust Algorithm for Signal Digital Detection on the Background of Non-Gaussian Passive Interferences

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***Abstract*—This paper proposes generalized mathematical model of different passive interferences and develops an effective algorithm of digital signal processing for detection on the background of them. Models of interferences as random process of K-distribution is used with parametrization for the unwanted reflections from atmosphere, land, and sea. Robust algorithm for signal detection on the background of such interferences, in particular in case of non-gaussian distribution, is developed. Its effectiveness is researched and confirmed.**

Keywords— digital signal processing, radar detection, clutter, algorithm design, algorithm analysis, ranking

I. INTRODUCTION

The problem of signal detection on the background of nonstationary interference arises in the design and operation of the vast majority of information measuring and radio engineering systems. Usually this is solved by constructing adaptive band-stop filters using Fourier transform and others. Most known methods and algorithms provide high effectivity in the case of Gaussian probability distribution of interferences, in particular passive interferences, or clutter. With deviations from the Gaussian distribution, which often happens in real situations, and especially under the influence of impulse noise, the effectiveness of such methods dramatically worsens and leads to information losses.

System noise immunity can be increased by applying robust and non-parametric methods and algorithms for signal processing. In the 70s, some attention of radar developers was attracted to robust statistics, the theory of ordinal statistics and rank rules. Some results in this direction are presented in [1], [2]. These works devise ideas of heuristic nonlinear processing using statistics of signals and noise based on ordinal statistics. Later these ideas seemed not enough important or difficult to implement and were not used in practice.

Today the reality is different. New level of science and technology has caused a great interest to robust non-parametric methods [3-7].

Normally different kinds of clutter with different statistic characteristics require different algorithms. There are known methods of clutter suppression based on moving target indication (MTI) that are often used in ground-based radar [8]. Such methods are not considered in this work because, in general case, a radar should effectively detect both moving and stationary targets.

This paper is devoted to the application of the generalized mathematical and computer models suitable for different background, in particular sea, land and rain, and, what is the main goal, to the development a robust signal processing algorithm, which aims to detect a signal against all these kinds of clutter with necessary quality of detection. That is, the purpose of this research is developing mathematical and computer models of clutter and creating robust algorithm for signal detection on the background of them using nonparametric rank approach.

II. GENERALIZED MODEL OF THE PASSIVE INTERFERENCES

A. K-distribution based model

Despite the problem of clutter investigation and simulation is studied at least during the half century the adequate clutter modelling task for the different scattering conditions such as sea, land and atmosphere is still actual. Among others, the promising is the clutter model on the base of compound K-distribution. It allows the physical interpretations unlike the Weibull or the Log-Normal statistics.

In case of sea clutter, the K-distribution describes two components of clutter fluctuations. One of them accounts for reflections from distributed elementary scatterers with comparatively small decorrelation time, while the second one represents a slow varying mean component that corresponds to the sea swell structure.

Another advantage of such model is the possibility to take into account and simulate the correlation properties [9] of the considered clutter conditions. The K-distribution based model can represent the Rayleigh process, whose mean power is averaged by the Gamma distribution. The compound form of K-distribution can be expressed [10] as:

$$f(E)=\int_0^\infty f(E\,|\,x)\,f_g(x)\,dx\,,\quad 0\le E\le\infty \tag{1}$$

where $f_g(x)=\frac{b^{\nu}}{\Gamma(\nu)}x^{\nu-1}\exp(-bx)$, $0 \le x \le \infty$ is the Gamma distribution of the local power with shape parameter ν and scale parameter b , and $f(E\,|\,x)=2E/x\cdot\exp\left(-E^2/x\right)$, $0 \le E \le \infty$ is a Rayleigh distribution of the mean power *x*.

The resulting expression for the K-distribution is:

$$f(E)=\frac{4b^{(\nu+1)/2}E^{\nu}}{\Gamma(\nu)}K_{\nu-1}\left(2E\sqrt{b}\right),\ 0 \le E \le \infty \qquad (2)$$

where $K_{\nu-1}(\cdot)$ is the modified Bessel function.

Supposing the proper definition of shape and scale parameters for the different clutter conditions, such as sea, land, and atmosphere, expression (2) represents the generalized model based on the K-distribution of clutter returns.

B. Sea clutter model parameters

Just two parameters need to be determined for the K-distribution in order to properly describe the amplitude sea clutter model, namely: the shape and scale parameters. The relation for the shape parameter ν definition that is based on the empirical model is proposed in [10]:

$$\log_{10}(\nu)=\frac{2}{3}\log_{10}\left(\phi_{gr}^{o}\right)+\frac{5}{8}\log_{10}\left(A_c\right)-k_{pol}-\frac{\cos\left(2\theta_{sw}\right)}{3}, \qquad (3)$$

where ϕ_{gr}^{o} is the grazing angle, A_c is the resolution area illuminated by the radar, k_{pol} is the factor dependent on the polarization of the sounding waveform and it is equal to 2.09 for the horizontal polarization, while changes to 1.39 for the vertical polarization case, θ_{sw} is the angle between the radar beam and swell directions in the presence of swell.

The shape ν and scale b factors of K-distribution are coupled by the average clutter reflected power $P_c=\nu/b$, and this power can be expressed by the radar equation, knowing radar parameters and σ^0 as the normalized sea clutter RCS. The normalized sea reflection is represented by several empirical models [11], among others the GIT model is the most popular. It allows to take into account sea surface parameters as well as wind speed and direction. Normalized RCS σ^0 for the horizontal (HH) and vertical (VV) polarizations can be represented as:

$$\sigma_{HH}^{0}=10\log_{10}\left(\lambda\phi_{gr}^{0.4}A_iA_uA_w\right)-54.09\ ;$$

$$\sigma_{VV}^{0}=\sigma_{HH}^{0}-1.05\ln\left(h_{av}+0.015\right)+1.09\ln(\lambda)+1.27\ln\left(\phi_{gr}+0.0001\right)+9.7,$$

where A_i , A_u , and A_w are the multipath interference parameter, wind direction dependence and the variation on sea state, correspondingly. These are defined by roughness σ_{ϕ} (defined by grazing angle, wind velocity *U* and λ), while $U=3.16s^{0.8}$, where s is the clutter criterion, which characterizes the sea state grade from 1 (calm-ripped) to 7 (high).

C. Land clutter model parameters

Radar ground return is described by σ°, scattering coefficient (scattering cross section per unit area). It depends on such ground parameters as complex permittivity (conductivity and permittivity), roughness of surface, inhomogeneity of subsurface and others. A lot of numerical data on the reflective ability of different kinds of the terrain can be found in the literature. However, for radar developers and for analysis, it is better to require that the characteristics of land clutter be determined regardless of the specific type of terrain.

There are two reasons for this:

1) the radar should support the required performance when located in various places and at different situations;

2) in many cases, even in relatively small areas (several kilometers), the terrain that is a source of clutter can be complex and mixed.

The book [10] provides information on reflections from land characterizing spatial amplitude distributions based on a large set of 30,246 measured histograms of clutter from 1,628 clutter areas classified as mixed rural areas. The influence of the grazing angle, terrain, carrier frequency, polarization and resolution are quantified regardless of the specific type of terrain.

Work [12] contains the empirical fitting results of the various land clutter conditions for the simpler dealing with Weibull distribution. However, our approach supposes using a generalized model based on K-distribution that will be suitable for all three wide classes of clutter under consideration (sea, land and precipitation). Taking this into account an adequate transition from Weibull to K-distribution model should be done.

The following relation between the K- and Weibull distributions shape parameters is very helpful to achieve desirable K-distribution parameters:

$$\frac{1}{\nu}=\frac{\Gamma\left(1+2a_w\right)}{2\Gamma^2\left(1+a_w\right)}-1 \qquad (4)$$

where the a_w is the Weibull distribution shape parameter.

Weibull shape parameter a_w data are given in [12] for different grazing angles.

D. Rain clutter model parameters

In the operational model we decided to limit simulation of the atmospheric clutter only by the case of rain as the most powerful source of weather clutter. The rain is characterized by the intensity of precipitation, or the rain rate. In the future, it is possible to consider more complicated and special cases taking into account spectral and polarimetric characteristics [13, 14] of signals and turbulence of the atmosphere [15].

For calculation of clutter intensity due to rain, we used the shape parameter of K-distribution ν =1.5, which was determined according to expression (4) for Weibull distribution shape parameter a_w=2. Pay attention that at a_w= 2 the Weibull distribution coincides with Rayleigh distribution. That is, at ν = 1.5 K-distribution is reduced to a distribution close to Rayleigh distribution for rain. Second K-distribution parameter, the scale coefficient, is selected in accordance with the reflected power, which is calculated based on radar equation for correspondent specific RCS of the rain (over the unit of volume) that is actually the relative reflectivity , which can be calculated at given rain rate as $\sigma_r = aR^b$ with $a = 1.3 \cdot 10^{-8}$ and $b = 1.6$ as empiric coefficients, and R is the rain rate in mm per hour.

III. ROBUST RANK DETECTION ALGORITHM

To create a rank algorithm, we consider two samples

$$E_1, E_2, ..., E_n \qquad (5)$$

and

$$\begin{pmatrix} e_{11} & \cdots & e_{1n} \\ \vdots & \ddots & \vdots \\ e_{m1} & \cdots & e_{mn} \end{pmatrix} \qquad (6)$$

Sample (5) is a realization of the signal $\overline{s}$ and clutter mixture envelope modelled by equation

$$E_i = \sqrt{(as_i + \upsilon_i)^2 + \varsigma_i^2} \qquad (7)$$

where υ_i and ς_i are normalized Gaussian samples (quadratures) with random Gamma distributed scale parameter, a is a signal parameter.

The clutter values are presented in the matrix (6), where rows are realizations of the clutter. The clutter values e_{ij}, i=$\overline{1,m}$ in the columns are obtained from the neighboring resolution volumes of E_i (5). They are K-distributed

$$f_{a=0}(E) = \frac{4b^{(\nu+1)/2} E^{\nu}}{\Gamma(\nu)} K_{\nu-1}\left(2E\sqrt{b}\right),\ 0 \le E \le \infty, \qquad (8)$$

where $K_{\nu-1}(\cdot)$ is the modified Bessel function.

If signal samples are present, E_i is distributed as Rice

$$f_{a\neq 0}(E) = \int_0^{\infty} \frac{E}{x} \exp(\frac{-(\mathrm{E}^2 + a^2)}{2x}) I_0(aE/x) \frac{b^{\nu}}{\Gamma(\nu)} x^{\nu-1} \exp(-bx)\, dx\ , \qquad (9)$$

with random scale parameter distributed by Gamma law.

Concerning sample $E_1, E_2, ..., E_n$, we check the hypothesis H_1: signal is present $(a \neq 0)$, against the hypothesis H_0: signal is absent $(a = 0)$. The sample $\{e_{ij}\}$, $i = \overline{1,m}$; $j = \overline{1,n}$ is a training sample and contains the clutter only. A nonparametric algorithm is based on rank statistics $\overline{R} = (R_1, R_2, ..., R_n)$, where ranks of sample values E_i are R_i, $i = \overline{1,n}$ and should be calculated by the formula

$$R_i = \sum_{j=1}^{m} U(E_i - e_{ji});\ U(E_i - e_{ji}) = \begin{cases} 1,\ E_i > e_{ji}; \\ 0, E_i < e_{ji}. \end{cases} \qquad (10)$$

Synthesis of the locally optimal free distribution rank algorithm for signal detection is based on the study of the distribution of ranks vector $\overline{R} = (R_1, R_2, ..., R_n)$, for the hypothesis H_1, when the sample contains a signal,

$$w(\overline{R} \mid a \neq 0) \qquad (11)$$

and constructing a locally optimal decision rule

$$\lambda(\overline{R}) = \frac{\partial w(\overline{R} \mid a)}{\partial a}\big|_{a=0} > V_d\,. \qquad (12)$$

To construct the distribution (10), we need to know the distribution of the signal sample for an alternative hypothesis H_1. Let $f\,(y,a)$ is one-dimensional probability distribution for H_1 , and $f\,(y,0)$ is a probability density for the hypothesis H_0. Then probabilities of ranks can be calculated as:

$$w_m(\mathrm{R}_i = l, f) = \mathrm{m}\binom{m-1}{l-1} \int_{-\infty}^{\infty} f(y,a)[F(y)]^{l-1}[1 - F(y)]^{m-l} dy, \qquad (13)$$

where $F(y)$ is cumulative distribution function (CDF) of K-distribution $F(y) = 1 - \frac{2}{\Gamma(\nu)}\left(\frac{by}{2}\right)^{\nu} K_{\nu}(by)$. The dependence of the values of the function on the rank l is calculated as

$$C_m(l,f) = \frac{\partial w_m(R_i = l, f \mid a)}{\partial a}\big|_{a=0} = \\ m\binom{m-1}{l-1} \int_{-\infty}^{\infty} J(E,a)[F(E)]^{l-1}[1 - F(E)]^{m-l} dE, \qquad (14)$$

where $J(\mathrm{E}) = \frac{\partial f(y,a)}{\partial a}\big|_{a=0}$ is the derivative of a one-dimensional probability distribution $f(E,a)$ over a signal parameter a at the point $a = 0$; $F(E)$ is one-dimensional CDF of the interference.

A generalized structural diagram of a locally optimal rank detector is shown in Fig. 1. Here we assume $C_m(l,f) = l$.

IV. MATLAB/SIMULINK MODELS

E. Model for Clutter Simulation

The clutter model simulator [16] consists of the following parts:

- radar parameters input unit;
- clutter mode selection and K-distribution model parameters calculation: sea clutter, land clutter, rain clutter, and clutter mode selection block;
- clutter generation;
- target parameters input and return signal generation;
- generation of mixed return signal with clutter and target;
- signal detection and clutter suppression using the locally optimal rank detector.

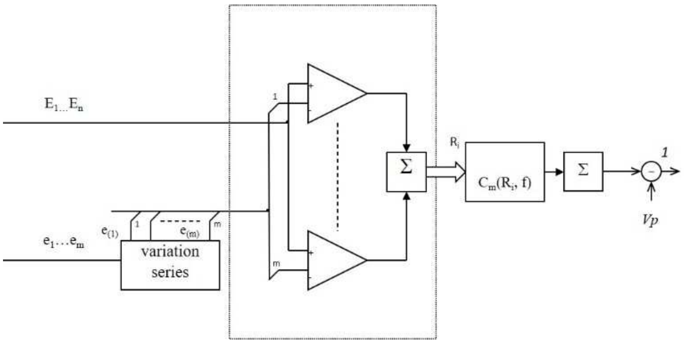

Fig. 1. Generalized structural diagram of a locally optimal rank detector.

F. Model for Detection Characteristics Evaluation

The model consists of the following parts: radar parameters input; clutter mode selection and K-distribution parameters calculation; clutter power estimation; target parameters input and return signal generation; generation of mixed return signal with clutter and target; clutter suppression using the locally optimal rank detector and detection probability estimation.

V. EXAMPLES OF RESEARCH RESULTS

The developed software allows to make research on clutter suppression and signal detection at different scenarios. Detection characteristics were estimated using statistical (Monte-Carlo) simulation.

In particular, the initial data are following:

Carrier Frequency is 10GHz;

Polarization is Vertical;

Peak Power is 900W;

Beam width is 4 degrees (symmetrical beam);

Duty factor is 0.1;

Tx and Rx Antenna Gain is 30dBi;

Noise figure is 4dB;

Pulse repetition frequency is 50 kHz, 10 kHz, and 1 kHz (three modes);

Signal bandwidth is 4MHz and 15MHz (two modes).

Max detection range is: 100 km for weather clutter case, 30 km for land clutter case, 55 km for sea clutter case.

The visualizing block implemented in the model represents the detection probability at the fixed slant range to the target as is shown in Fig. 2.

The vertical red line in Fig.2 indicates the detection probability for the target radar cross section (RCS). The desired signal-to-clutter ratio (SCR) can be selected using the appropriate block in Simulink software.

Characteristics of harmonic signal detection against the background of passive interference (clutter) were got using two algorithms:

1) the proposed rank nonparametric algorithm;

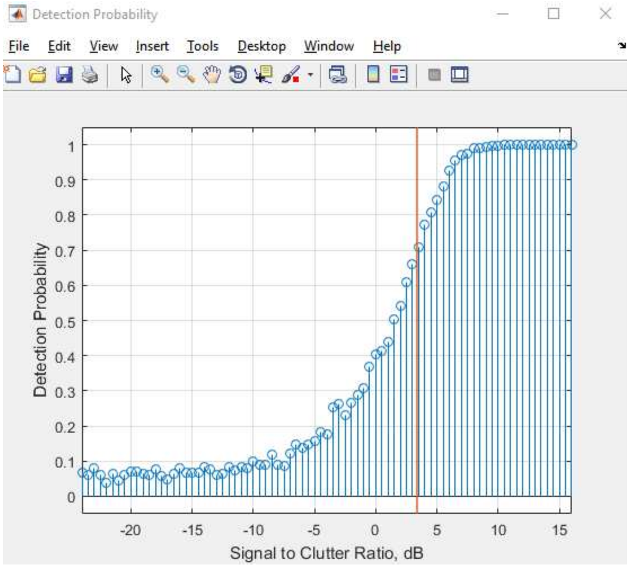

Fig. 2. An example of representation a detection characteristic using statistical Monte Carlo simulation.

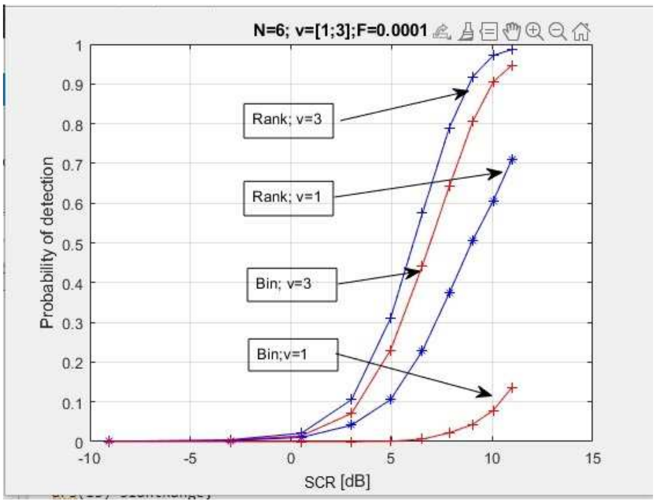

Fig. 3. Detection characteristics of rank and binary algorithms for different shape parameters ν Sample size N=6. False alarm probability F=10^{-4}.

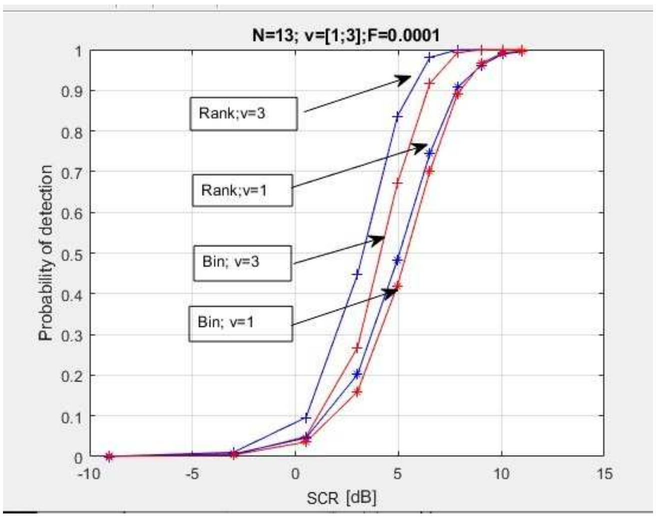

Fig. 4. Detection characteristics of rank and binary algorithms for different shape parameters ν Sample size N=13. False alarm probability F=10^{-4}.

2) the classical binary non-adaptive integrator synthesized for the case of aprioristic certainty [2].

The results are presented in Fig. 3 and 4. The clutter is distributed over the K-distribution with two values of the shape parameter v = 1 and v = 3. The sample size takes two values: N = 6 and N = 13.

One can see from the plots that the ranking algorithm is more efficient than a non-adaptive binary integrator. Numerous calculations done under different conditions confirm that this result is valid at all cases. At small sample sizes the advantage is greater.

VI. CONCLUSION

The generalized math model for the sea, land, and atmosphere clutter has been proposed on the base of the K-distribution and implemented as the computer software [16]. This model has been adapted for different kinds of clutter: sea, characterized by the state of sea (grade); weather, characterized by the rain rate; land, characterized by relative reflectivity of the surface. The developed model is reasonable to be used for investigation of different signal processing algorithms [17] of clutter suppression or signal detection on the background of clutter.

The locally optimal rank algorithm has been developed for nonparametric robust detection. It is suitable for suppressing different kinds of clutter especially under the condition of non-Gaussian statistics that often happens in real situations [18].

The unique software tool for investigation of different situations related with clutter suppression has been created. This tool includes Matlab/Simulink model that allows to research the detection characteristics for estimating clutter suppression effectivity. The developed software has friendly interface and is suitable for further and enhancing.

The effectivity analysis of clutter suppression has been conducted for numerous essential situations under conditions of different kinds of clutter, wide spectrum of radar parameters, target characteristics, and features of observation scenarios. The proposed detection algorithm has demonstrated its high effectivity under different conditions and can be useful for various applications [19 - 22].

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REFERENCES

[1] H. Rohling, “Radar CFAR Thresholding in Clutter and Multiple Target Situations,” IEEE Trans. on AES, Vol. 19, No. 4, pp. 608-621, July 1983.

[2] E.A. Kornil'ev, I.G. Prokopenko, and V.M. Chuprin, Stable algorithms in automated information processing systems. Kyiv, Ukraine: Tekhnika, 1989, 224 pp. (in Russian).

[3] B. Leibe, A. Leonardis, and B. Schiele, “Robust object detection with interleaved categorization and segmentation,” International Journal of Computer Vision (IJCV), 77 (1-3), pp. 259-289, 2008.

[4] M. Tao, F. Zhou, J. Liu, Y. Liu, Z. Zhang, and Z. Bao, “Narrow-Band interference mitigation for SAR Using Independent Subspace Analysis,” IEEE trans. GRS, vol. 52, no. 9, pp. 5289-5301, Sep. 2014.

[5] L.P. Ligthart, F.J. Yanovsky, and I.G. Prokopenko, “Adaptive algorithms for radar detection of turbulent zones in clouds and precipitation,” IEEE Trans. on AES, Vol. 39, No1, pp. 357-367, 2003.

[6] R.B. Sinitsyn and F.J Yanovsky, “Acoustic noise atmospheric radar with nonparametric copula-based signal processing,” Telecommunications and Radio Engineering, Vol. 71, No. 4, pp. 327-335, 2012.

[7] R.B. Sinitsyn and F.J. Yanovsky, “MIMO radar copula ambiguity function,” European Microwave Week, EuMW 2012, 9th European Radar Conference, EuRAD 2012, pp. 146-149, 2012.

[8] I.G. Prokopenko, I.P. Omelchuk, and Y.D. Chyrka, RADAR Signal Parameters Estimation in the MTD Tasks, Intl Journal of Electronics and Telecommunications, 2012, Vol. 58, No. 2, pp. 159–164. DOI: 10.2478/v10177-012-0023-5

[9] C.J. Oliver and R.J.A. Tough, “On the Simulation of Correlated K-distributed Random Clutter,” Optica Acta: International Journal of Optics, Vol. 33, No 3, pp. 223-250, 1986.

[10] K.D. Ward, R.J.A. Tough, and S. Watts, “Sea clutter: Scattering, the K distribution and radar performance,” Waves in Random and Complex Media, Vol. 17, Issue 2, pp. 233-234, 2007.

[11] S.Watts, K.Ward, M.Greco, “Radar Performance in Clutter – Modelling, Simulation and Target Detection Methods,” European Radar Conference *EuRAD*, 2016. Available: https://intranet.birmingham.ac.uk/eps/documents/public/emuw2/WF02.pdf

[12] J. Barrie Billingsley, Low angle radar land clutter: measurements and empirical models, USA: William Andrew Publishing, 2002.

[13] F. J. Yanovsky, “Inferring microstructure and turbulence properties in rain through observations and simulations of signal spectra measured with Doppler–polarimetric radars,” In: Polarimetric Detection, Characterization, and Remote Sensing, M. Mishchenko, Y. Yatskiv, V. Rosenbush, and G. Videen (eds.), NATO Science for Peace and Security Series C: Environmental Security, Springer Science+Business Media B.V., pp. 501-542, 2011.

[14] A.N. Rudiakova, Y.A. Averyanova, and F.J. Yanovsky, “Advanced Spectral Model of Doppler-Polarimetric Meteorological Radar Signal,” The 15th European Radar Conference, pp.107-110, 2018.

[15] D.N. Glushko and F.J. Yanovsky, “Analysis of differential Doppler velocity for remote sensing of clouds and precipitation with dual-polarization S-band radar,” International Journal of Microwave and Wireless Technologies, Vol. 2, issue 3-4, pp. 391-398, 2010.

[16] Felix Yanovsky, Igor Prokopenko, Anna Rudiakova, and Huinam Rhee, Generalized Computer Model of Sea, Land and Atmospheric Clutter, International Radar Symposium (IRS-2022), Microwave and Radar Week 2022, Gdansk, Poland, September, 2022, 6 pp., in press.

[17] I.G. Prokopenko, "Robust methods and algorithms of signal processing," 2017 IEEE Microwaves, Radar and Remote Sensing Symposium (MRRS), 2017, pp. 71-74, doi: 10.1109/MRRS.2017.8075029.

[18] F.J. Yanovsky, C.M.H. Unal, H.W.J. Russchenberg, and L.P. Ligthart, Doppler-Polarimetric Weather Radar: Returns from Wide Spread Precipitation, Vol. 66, Issue 8, 2007, pp. 715-727. DOI: 10.1615/TelecomRadEng.v66.i8.20

[19] Y. Averyanova, A. Averyanov and F. Yanovsky, "The approach to estimating critical wind speed in liquid precipitation using radar polarimetry," 2012 International Conference on Mathematical Methods in Electromagnetic Theory, 2012, pp. 517-520, doi: 10.1109/MMET.2012.6331259.

[20] A. I. Nosich, Y. M. Poplavko, D. M. Vavriv and F. J. Yanovsky, "Microwaves in Ukraine," in IEEE Microwave Magazine, vol. 3, no. 4, pp. 82-90, Dec. 2002, doi: 10.1109/MMW.2002.1145680.

[21] I. Prokopenko, Nonparametric Change Point Detection Algorithms in the Monitoring Data, Book Chapter in Lecture Notes on Data Engineering and Communications Technologies, 2021, 83, pp. 347–360.

[22] I.G. Prokopenko, Nonparametric algorithms for detection of radar markov signals against the background of markov noise, Proceedings of the International Radar Symposium, IRS-2020, October 2020, pp. 356–361.