# Adaptive algorithms for the detection of radar signals against the background of broadband interferences

Igor Prokopenko[1,†], Anastasiia Dmytruk[1,*,†] and Alina Osipchuk[1,†]

[1] *National Aviation University, Liubomyra Huzara Ave., 1, Kyiv, 03058, Ukraine*


### Abstract

The paper presents the results of research on adaptive algorithms for detecting radar signals against the background of broadband interference. Since modern radar systems operate in an intense electromagnetic environment, which includes dynamically changing and complex interference, the use of classical detection algorithms often turns out to be insufficiently effective. This necessitates the introduction of adaptive approaches to increase the reliability and accuracy of signal detection. The paper analyzes adaptive detection algorithms synthesized based on the Neyman-Pearson criterion with maximization of the likelihood function and also considers adaptive filtering algorithms, which are key elements of the structure of these algorithms. The conducted modeling demonstrates that adaptive algorithms significantly increase the effectiveness of radar signal detection in complex conditions of broadband interference, which confirms their promising application in solving the problem of detection.


### Keywords

adaptive detection algorithms, broadband interference, autoregressive model, adaptive filter, maximum likelihood method

## 1. Introduction

In modern radar systems, the task of detecting signals against the background of complex obstacles remains relevant to this day. Radar systems, especially those focused on moving target detection (MTD), often encounter various types of interference, which degrades their performance. These sources can include both Gaussian and non-Gaussian interference, such as Laplace-distributed or K-distributed interference, which is often seen in dynamic environments or the presence of electronic warfare (EW) countermeasures. Such disturbances are usually broadband and have complex statistical properties that complicate the task of detecting useful signals. In these conditions, traditional detection methods based on periodic compensation and classical filtering algorithms demonstrate limited effectiveness due to their inability to adapt to the changing conditions of the interfering environment [1]. In turn, this requires the development of more flexible approaches to signal detection [2].

In this case, the use of adaptive detection algorithms capable of adjusting their parameters according to the characteristics of interferences is of particular interest [3, 4, 5]. The basis of these algorithms is statistical optimization criteria, such as the Neyman-Pearson criterion and the maximum likelihood method, which allow the synthesis of interference-resistant detection algorithms [6, 7, 8, 9]. Thus, the work [10] analyzes various approaches to solving the detection problem, in particular methods of maximum likelihood which provide optimal results in situations with unknown signal and interference parameters. According to this, adaptive algorithms can

*ADP'24: International Workshop on Algorithms of Data Processing, November 5, 2024, Kyiv, Ukraine*

* Corresponding author.
† These authors contributed equally.
igorprok48@gmail.com (I. Prokopenko); gyhyre@gmail.com (A. Dmytruk); alina.osipchuk2012@gmail.com (A. Osipchuk)
0000-0003-4169-3774 (I. Prokopenko); 0000-0002-6410-4680(A. Dmytruk); 0000-0002-9053-2072 (A. Osipchuk)

increase the accuracy of signal detection even in complex conditions, using information about the distributions of the interference and the useful signal.

In turn, the adaptability of these algorithms is provided by the use of adaptive filters in their structure, which, based on current estimates of interference parameters, adjust their coefficients to minimize their impact on the process of detecting a useful signal [11]. In particular, it is worth noting that the estimation of the parameters of random processes is an important problem in many applied problems of radio electronics [12].

The practical value of adaptive signal processing algorithms is highlighted in [13, 14], where their ability to reduce interference and improve the signal-to-interference ratio (SIR) is demonstrated. This improvement is a critical factor in ensuring accurate signal detection against a backdrop of broadband interference. The researchers also emphasize that properly tuning the parameters of adaptive filters can significantly enhance system efficiency, which is crucial for their performance in dynamically changing environments. In this way, a related problem is formed, which is based on the synthesis of the optimal algorithm for estimating the parameters of adaptive filters. One of the fundamental works in this field is [15], which outlines the basics of the theory of adaptive filtering, including various algorithms for evaluating filter parameters. Especially important is the fact that the parameter estimation algorithm must be not only accurate but also integrated into the general structure of the detection algorithm.

Considering the above, the purpose of this paper is to review and analyze the effectiveness of synthesized adaptive algorithms [16, 17, 18, 19] for detecting radar signals against the background of broadband interference to increase the accuracy of signal detection and reduce the level of false alarms.

## 2. Adaptive detection algorithms

### 2.1. Theoretical background

Since the signal-interference mixture at the input of the receiver is an implementation of a random process, statistical methods are key tools for solving the problem of detecting moving targets against the background of passive interference.

Accordingly, the formulation of the detection problem is formulated as a statistical problem, within which two hypotheses are put forward for the input realization of the signal. Hypothesis $H_0$ assumes that the input realization contains only interference, while the alternative hypothesis $H_1$ states that the sample contains both interference and signal [20]. Formed hypotheses are the basis for the synthesis of the detection algorithm because they contain information about the influence of the presence of a signal on a sample of a random implementation, which is presented in the form of the density of probability distributions, which, with a fixed implementation of the sample, represent a likelihood function. At the same time, taking into account the condition of insufficient a priori data, when solving the problem of synthesizing the optimal structure of detection algorithms, it is advisable to use the Neyman-Pearson criterion [21], according to which it is necessary to describe the density of the mixture of signal and interference for the cases of the presence and absence of the signal and calculate likelihood ratio:

$$L(\bar{x},\bar{\vartheta}) = \frac{f_1(\bar{x},\bar{\vartheta}|H_1)}{f_0(\bar{x},\overline{\vartheta}|H_0)}, \tag{1}$$

where $f_0(\bar{x},\bar{\vartheta},H_0), f_1(\bar{x},\bar{\vartheta},H_1)$ are the probability density functions of the statistical hypotheses $H_0$ and $H_1$ in the presence and absence of the signal, respectively, $\bar{\vartheta}$ is the vector of parameters of the mixture of signal and interference.

Since it is necessary to ensure compliance with the condition of providing the minimization of the probability of errors of the second type at a fixed level of the probability of errors of the first type, which corresponds to the criterion of efficiency in the conditions of limited a priori information, when forming the detection algorithm, it is advisable to use the maximum likelihood method (MLM). This method consists of choosing a hypothesis that maximizes the likelihood ratio (1), that is, in finding the maximum of the derivative (1) according to the signal parameter and the vector of interference parameters:

$$L(\bar{x},\bar{\vartheta}) = \frac{\max_{\bar{\vartheta}} f_1(\bar{x},\bar{\vartheta}|H_1)}{\max_{\bar{\vartheta}} f_0(\bar{x},\overline{\vartheta}|H_0)}. \quad (2)$$

Taking into account the insufficiency of a priori data, there is a related problem of estimating the vector of unknown parameters of obstacles. For the further synthesis of adaptive detection algorithms, an empirical Bayesian approach is used, which allows refining parameter estimates based on a posteriori information.

Based on the formed likelihood ratio (2), a statistic of random values is obtained, which is compared with the decision-making threshold $V_{th}$, according to which a decision is made about the presence or absence of a signal:

$$L(\bar{x},\bar{\vartheta}) > V_{th} \begin{vmatrix} 1, & if\ L(\bar{x}) \geq V_{th}, \\ 0, & if\ L(\bar{x}) < V_{th}. \end{vmatrix} \quad (3)$$

The procedure described above is the basis of synthesized adaptive detection algorithms. However, depending on the specifics of a particular task, the structure of algorithms may undergo certain modifications. For example, the nature of the signal or interference, and the level of available a priori information can affect the choice of optimization criteria, the method of evaluating the parameters of adaptive filters.

## 2.2. An adaptive signal detection algorithm against the background of the Gaussian autoregressive interference model

One of the important stages in synthesizing algorithms is the mathematical modeling of the signal and interference. In the context of radar detection tasks, the harmonic signal is one of the most common models [19]:

$$S = U\cos(\omega_0 t + \varphi). \quad (4)$$

In turn, for mathematical modeling of interference, it is advisable to use autoregressive (AR) models, which represent a signal as a linear combination of its past values, i.e. in such a way that the current value of the signal is the sum of its previous values with a given random generation process [22]. AR models provide a flexible tool for describing various types of interference, particularly correlated interference, and interference with a complex statistical structure, making them suitable for radar detection and analysis of broadband interference [23]. Mathematically, the AR model of order $k$ can be described by the following equation:

$$y_i = \sum_{j=1}^{k} a_j\, y_{i-j} + \varepsilon_i, \quad (5)$$

where $y_i$ are signal counts at the current time $i$, $a_j$ are the autoregressive coefficients, $\varepsilon_i$ is generating random process.

Given that the signal obtained as a result of reflection is a mixture of useful signal and interference, the additive model of the mixture of signal and interference (6) is taken into account when synthesizing algorithms, which allows mathematical formalization of the signal reception process, in which interference is superimposed on the signal:

$$x_i = bS_i + y_i, \quad (6)$$

where $b$ is signal parameter that determines the amplitude of the received signal.

Thus, based on the generalized detection algorithm described above (3), the structure of the local-optimal adaptive signal detection algorithm against the background of the Gaussian autoregressive interference model is formed as described in [16], and which can be mathematically formalized by the expression:

$$\frac{\partial}{\partial b}\ln\left(L(x_1,\dots,x_n,b)\right)_{|b=0} =$$
$$= \sum_{i=k+1}^{n}\left((x_i - \sum_{j=1}^{k} a_j^* x_{i-j})\cdot(S_i - \sum_{j=1}^{k} a_j^* S_{i-j})\right) > V_{th}(\overline{S},\overline{a^*},\sigma), \quad (7)$$

where $a_j^*$ are the estimated autoregressive coefficients, $\sigma$ is the variance of a random process.

The synthesized algorithm can be presented in the form of a scheme adaptive detector (Figure 1), where the key elements are the unit for evaluating the interference parameters, adaptive rejection filters, and the decision-making system.

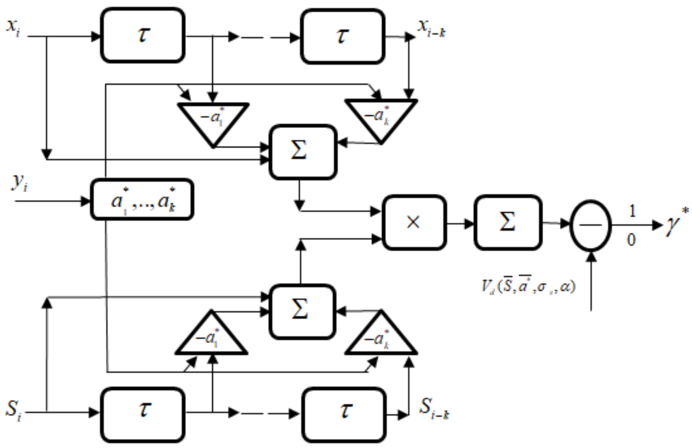



Figure 2: Block scheme of a deterministic signal adaptive detector.

### 2.3. An adaptive algorithm for detecting a harmonic signal with an unknown phase against a background of Gaussian correlated interference in the presence of impulse interference

To address the task of detecting a harmonic signal with a known frequency but unknown phase, the detection algorithm must exhibit phase invariance. To achieve this, the likelihood ratio is reformulated by decomposing the signal into its quadrature components, enabling the algorithm to be expressed in terms of amplitude and phase, as outlined in [17]. This method ensures phase invariance, allowing for the synthesis of a detection algorithm that remains effective regardless of phase variations, thereby enhancing the algorithm's robustness in practical applications.

Thus, the detection algorithm is reduced to the form:

$$\ln\left(L(x_1,\dots,x_n,\bar{\vartheta})\right) = R(\bar{x},\omega) > V_{th}(p,\overline{a^*}), \quad (8)$$

where $p$ is the probability of pulse clutter action, $R(\bar{x},\omega) = \sqrt{A(\bar{x},\omega)^2 + C(\bar{x},\omega)^2}$, $A(\bar{x},\omega) = \sum_{i=k+1}^{n}\left(\left(x_i - \sum_{j=1}^{k} a_j x_{i-j}\right)\left(cos(\omega t_i) - \sum_{j=1}^{k} a_j\, cos\left(\omega t_{i-j}\right)\right)\right)$, $C(\bar{x},\omega) = \sum_{i=k+1}^{n}\left(\left(x_i - \sum_{j=1}^{k} a_j x_{i-j}\right)\left(sin(\omega t_i) - \sum_{j=1}^{k} a_j\, sin\left(\omega t_{i-j}\right)\right)\right)$, $\overline{a^*}$ is vector of estimated autoregressive coefficients.

As a result, the structure of the adaptive detector, the scheme of which is shown in Figure 2, is formed [17].

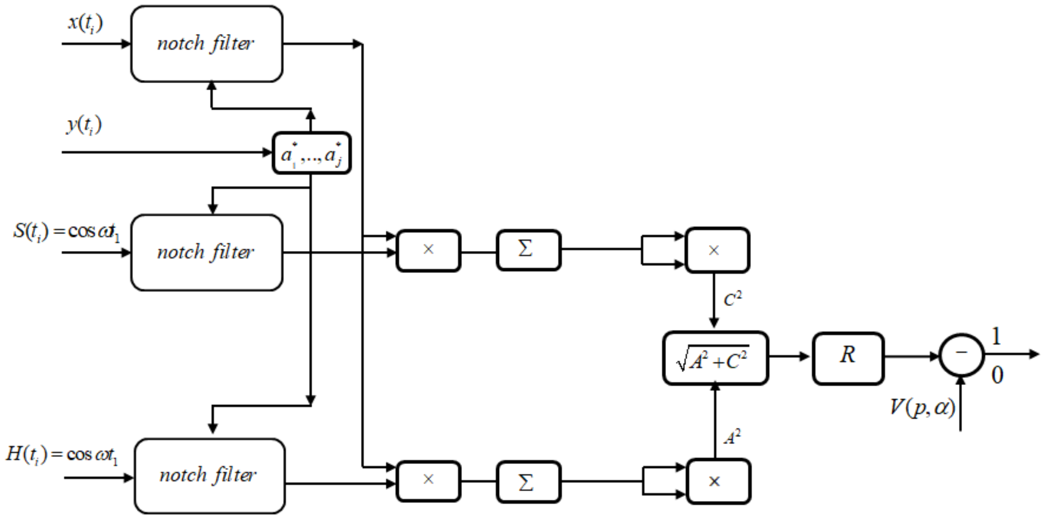


Figure 2: Structural diagram of an adaptive phase-invariant detector.

## 2.4. An adaptive signal detection algorithm against the background of the non-Gaussian autoregressive interference model

The relevance of synthesizing detection algorithms based on non-Gaussian models is that real obstacles often have more complex statistical properties than the Gaussian model predicts. In this regard, when solving this problem, the process described by the Laplace distribution was used as a mathematical model of disturbances. This approach allows for more accurate modeling of samples of the generating random process, considering the influence of deviations characteristic of real obstacles, as described in the paper [18].

According to the method of maximum likelihood, the synthesis of a decisive rule for detecting a signal of a known form against the background of a non-Gaussian autoregressive disturbance with unknown coefficients consists of finding the maximum of the derivative according to the signal parameter $b$ and the vector of disturbance parameters $\overline{a^*}$. As a result, a test statistic is formed, which, when compared with the decision-making threshold, is a detection algorithm, which for the given task can be represented by the expression:

$$\frac{\partial}{\partial b}\ln\left(L(x_1, \ldots, x_n, b)\right)_{|b=0} =$$
$$= \sum_{i=k+1}^{n}\left(sgn(x_i - \sum_{j=1}^{k} a_j^* x_{i-j}) \cdot (S_i - \sum_{j=1}^{k} a_j^* S_{i-j})\right) > V_{th}(\overline{S}, \overline{a^*}, \lambda), \quad (9)$$

where $sgn$ is signum function, $\lambda$ is scale parameter of Laplace distribution that depends on the autoregressive coefficients.

The described detection algorithm is the basis for forming the structure of the adaptive detector (Figure 3) [18].

## 2.5. An adaptive algorithm for detecting a harmonic signal with an unknown phase against the background of non-Gaussian impulse interference

When synthesizing the detection algorithm, following the formulated problem, it was taken into account that the samples of the generating random process are formed as a mixture of an uncorrelated Gaussian process and a Laplace impulse process. Based on this, the corresponding likelihood functions used in the formation of the likelihood ratio (3) were formed and described. At the same time, similar to the problem that was considered above when detecting a harmonic signal characterized by a known frequency but an unknown phase it is advisable to rewrite the likelihood ratio by decomposing the signal into quadrature components. This approach is discussed in detail in the article [19].

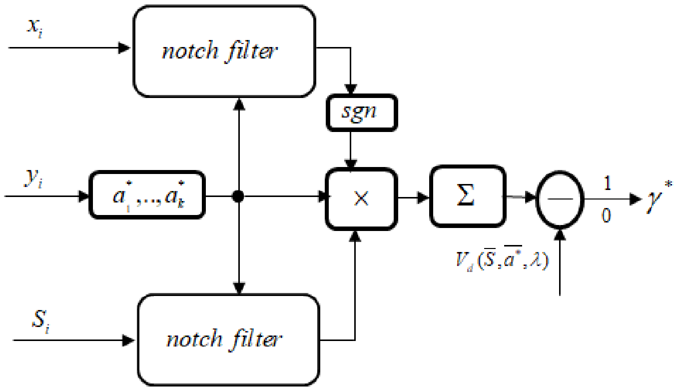



Figure 3: Structural diagram of a deterministic signal detector against the background of a non-Gaussian autoregressive interference model.

Thus, as it was described in [19], taking the derivative of the formed likelihood ratio by the signal parameter at the point $b = 0$, a local optimal solution is obtained, which can be described by expression:

$$\frac{\partial}{\partial b} ln\big(L(x_1, \ldots, x_n)\big) = \sum_{i=1}^{n} \frac{d}{db} ln\left(\frac{bR(x_i) + Q_i}{1 + Q_i}\right)|_{b=0} = \\ = \sum_{i=1}^{n} \frac{R(x_i)}{Q_i} = \sum_{i=1}^{n} \Phi(R_i, Q_i) > V(p, \alpha). \tag{10}$$

As a result, the structure of the scheme of the locally optimal algorithm (10) is formed, which is shown in Figure 4 [19].

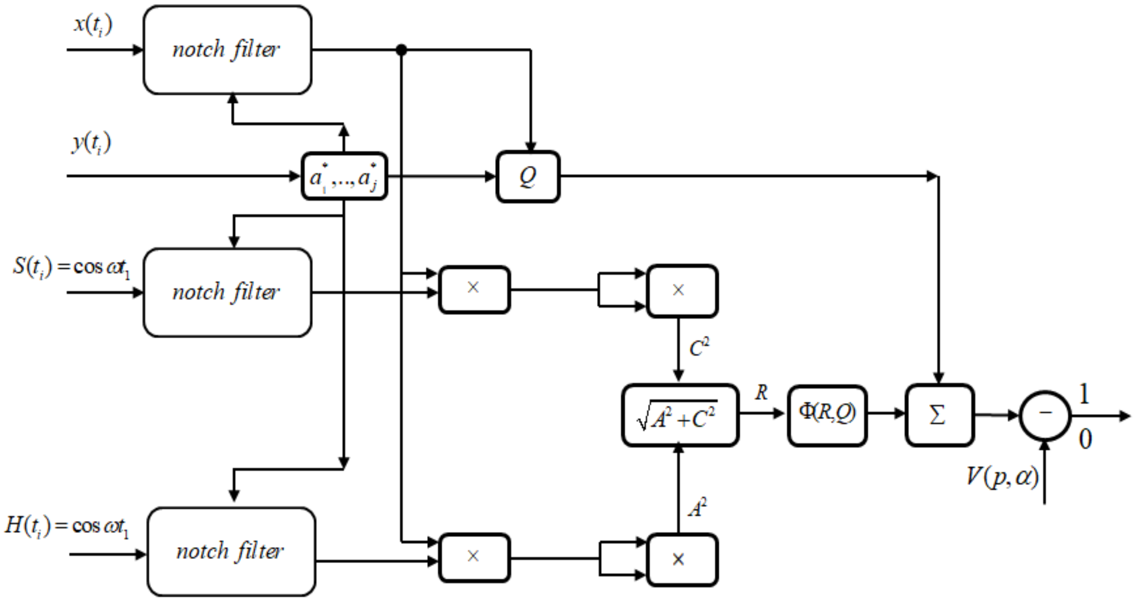



Figure 4: Structural diagram of an adaptive detector of a harmonic signal with an unknown phase against the background of a non-Gaussian autoregressive impulse interference model.

## 3. Algorithms for estimating the parameters of the autoregressive model of interference

A common feature of the synthesized algorithms [16, 17, 18, 19] is the presence of a stage of estimating autoregressive coefficients, which ensures their adaptability. In this connection, a related task arises; the synthesis of an optimal algorithm for estimating the parameters of the autoregressive model of interferences, according to the algorithms described above.

The estimation of parameters, which ensures the adaptability of the algorithm, is based on the use of a sample containing only the disturbance (5).

Since the parameters are random variables, the algorithm is formed based on the empirical Bayesian method, which involves estimating the unknown parameters of the interference by the method of the maximum posterior probability density, according to which it is possible to form a general equation for obtaining an estimate of the parameters:

$$\frac{\partial}{\partial a_j}\ln\, L(y_{k+1},\ldots,y_m|y,\ldots,y_k,\overline{a}) = 0, j = \overline{1,k}. \tag{11}$$

Since in [16, 17] the disturbances are described by an autoregressive Gaussian process, the parameters can be estimated using the method of least squares. This is explained by the fact that for Gaussian processes the likelihood function is quadratic concerning the parameters, that is, the maximization of this function by the MMP leads to the minimization of the sum of the squares of the deviations, which is the basis of the least squares method:

$$lnL = \sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{k} a_j y_{i-j}\right)^2 \rightarrow min. \tag{12}$$

To find the minimum of the function (12), the partial derivatives are calculated according to the autoregression parameters (13), and a system of equations is formed that is solved according to the chosen method of solving linear algebraic equations and is obtained $a_j^*$, which is a solution of the set of probability equations:

$$\sum_{i=k+1}^{n}\left(y_i - \sum_{j=1}^{k} a_j y_{i-j}\right)y_{i-l} = 0, \qquad l = \overline{1,k}. \tag{13}$$

In turn, for the algorithms described in [18, 19], given the non-Gaussian distribution of disturbances, the procedure for estimating the unknown parameters of the autoregressive process requires the introduction of special functions.

Based on equation (11), taking into account the peculiarities of the Laplace probability distribution, it is possible to use the method of the least absolute deviation:

$$lnL = \sum_{i=1}^{n}\left|y_i - \sum_{j=1}^{k} a_j y_{i-j}\right|^2 \rightarrow min. \tag{14}$$

Similarly to (13), to find the minimum of (14), it is necessary to calculate the partial derivatives for the unknown parameters, according to which we obtain:

$$\sum_{i=k+1}^{n} sgn\left(y_i - \sum_{j=1}^{k} a_j y_{i-j}\right)y_{i-l} = 0, \qquad l = \overline{1,k}. \tag{15}$$

According to the expression (15) for estimating the unknown parameters, when using (14), a system of nonlinear equations is formed, for the solution of which the Newton-Raphson method is used, as described in [19].

## 4. Computer simulation

The effectiveness of the synthesized algorithms is investigated using computer simulation, which allows for a detailed assessment of their performance.

The results of computer modeling of the adaptive algorithm [16] are shown in Figure 5, 6, 7 where the spectra of the signal and interference mixture before filtering (Figure 5) and after filtering (Figure 6) and the detection characteristics (Figure 7) of the proposed algorithm are presented.

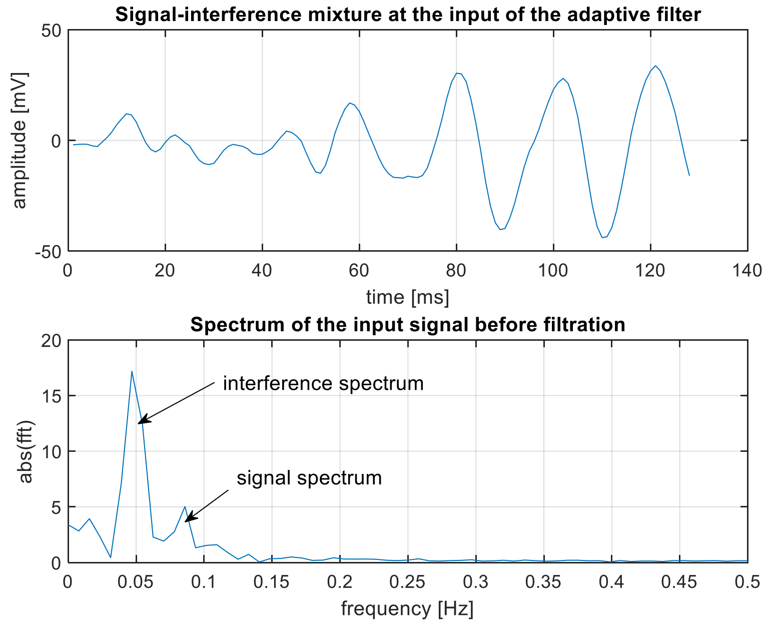



Figure 5: Input time and spectrum plots of the mixture of signal and interference before filtering. $N = 128;\ a = [1.9;\ -0.99]$.

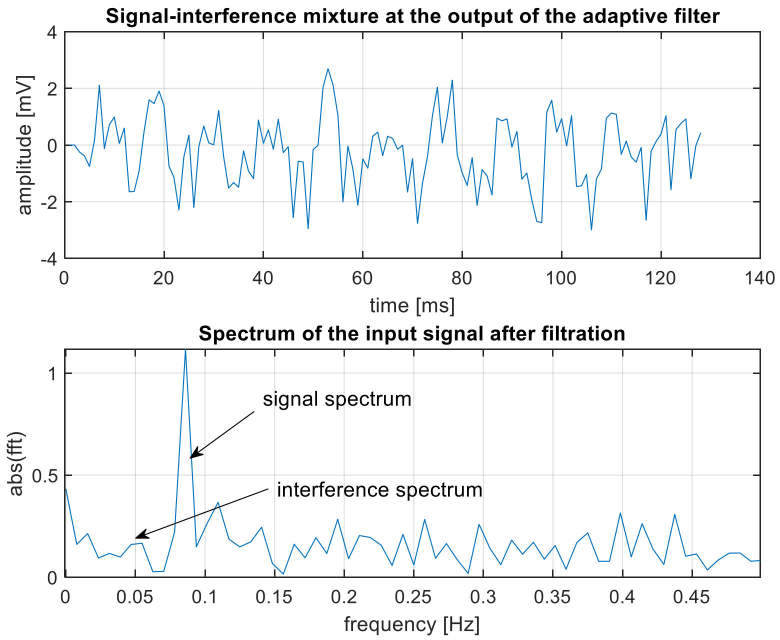



Figure 6: Output time and spectrum plots of the mixture of signal and interference after filtering. $N = 128;\ a = [1.9;\ -0.99]$.

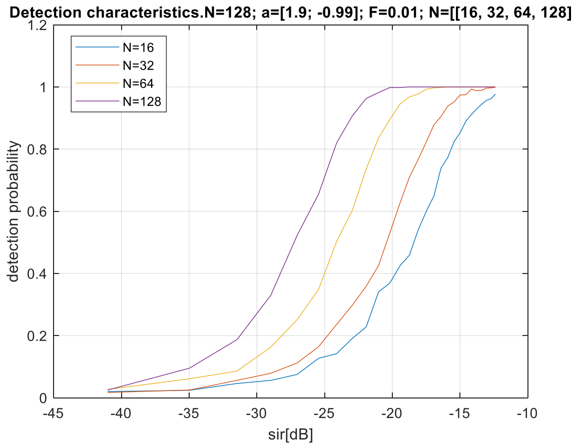



Figure 7: Detection characteristics of algorithm (7) at different sample size $N = [16;\ 32;\ 64;\ 128], F = 0.01$.

The results of computer simulations for the adaptive detection algorithm [17] are presented in Figures 8, 9, and 10, illustrating the signal and interference mixture spectra before filtering (Figure 8), after filtering (Figure 9), as well as the detection characteristics of the proposed algorithm (Figure 10).

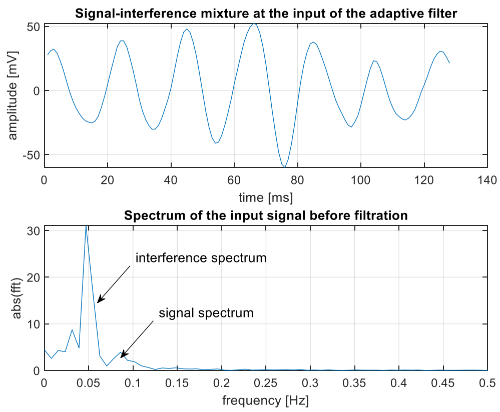



Figure 8: Input time and spectrum plots of the mixture of signal and interference before filtering. $N = 128;\ a = [1.9;\ -0.99]$.

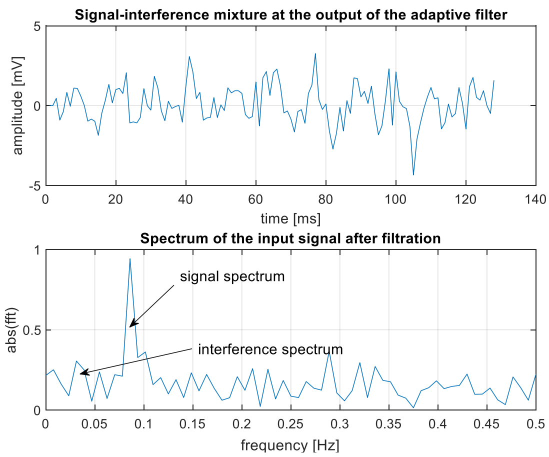



Figure 9: Output time and spectrum plots of the mixture of signal and interference after filtering. $N = 128;\ a = [1.9;\ -0.99]$.

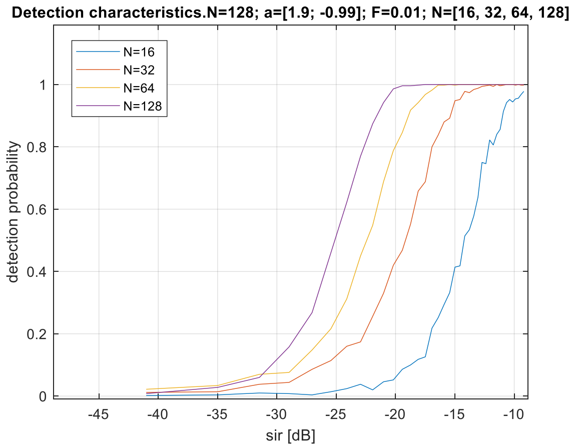



Figure 10: Detection characteristics of algorithm (8) at different sample size $N = [16;\ 32;\ 64;\ 128], F = 0.01$.

The results of computer simulations for the adaptive detection algorithm [18] are shown in Figures 11, 12, and 13, where Figure 11 presents the spectra of the signal and interference mixture before filtering, Figure 12 shows the spectra after filtering, and Figure 13 illustrates the detection characteristics of the proposed algorithm.

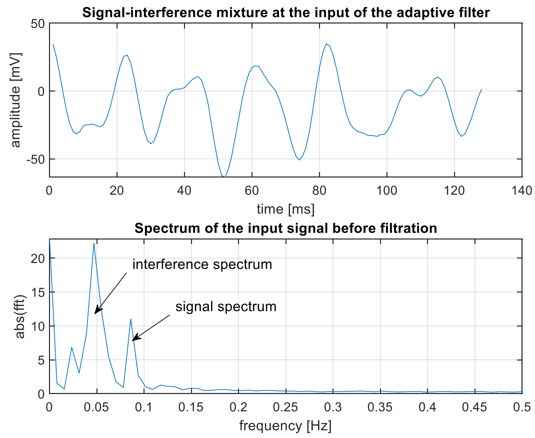



Figure 11: Input time and spectrum plots of the mixture of signal and interference before filtering. $N = 128;\ a = [1.9;\ -0.99]$.

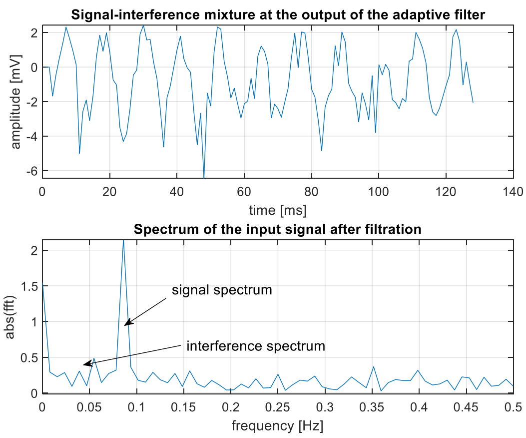



Figure 12: Output time and spectrum plots of the mixture of signal and interference after filtering. $N = 128;\ a = [1.9;\ -0.99]$.

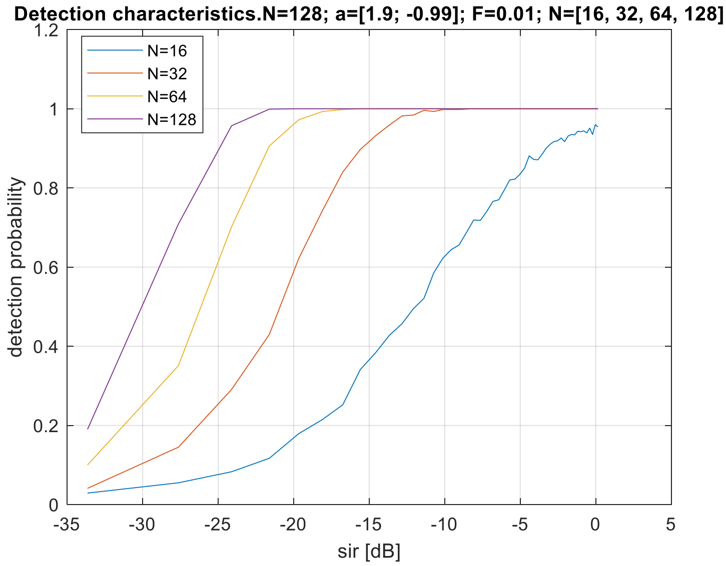



Figure 13: Detection characteristics of algorithm (9) at different sample size $N = [16;\ 32;\ 64;\ 128], F = 0.01$.

The results of computer modeling for the adaptive algorithm (10) are illustrated in detail in the article [19]. In this work, we will only give the characteristics of the detection of the synthesized algorithm, which is demonstrated in Figure 14 [19].

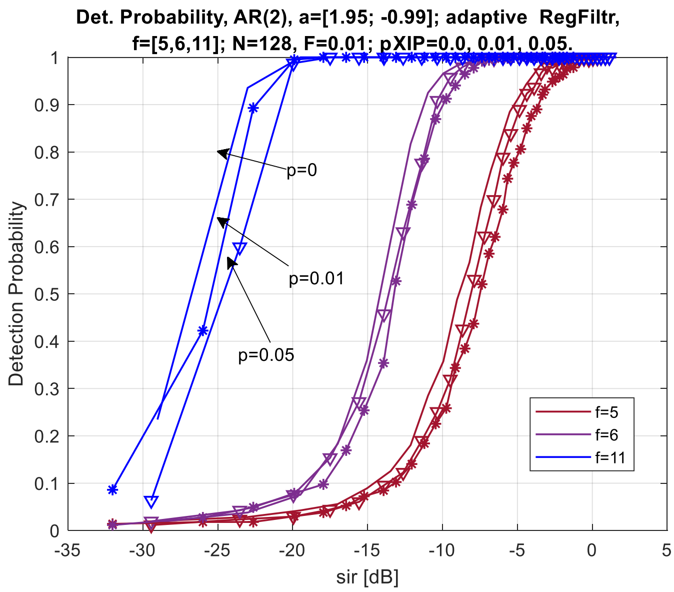
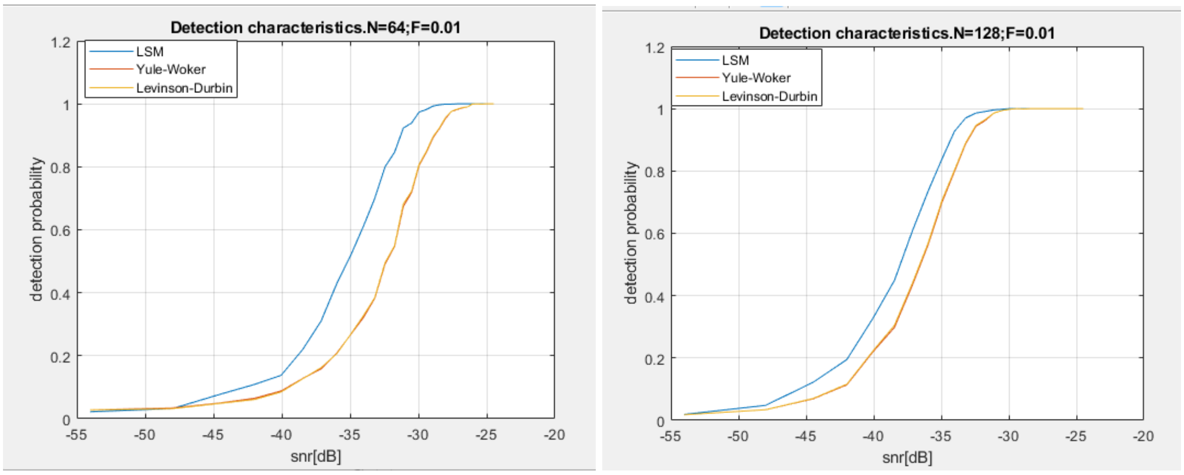



Figure 14: Detection characteristics of algorithm (10).

The effectiveness and expediency of using the maximum likelihood method (MLM) for estimating the parameters of autoregressive models of interferences were evaluated by comparing it with the traditional Yule-Walker and Levinson-Durbin methods using computer simulations. As shown in [17], research results confirm that the estimates obtained by the MLM method are statistically sound, asymptotically unbiased, and have better convergence compared to classical methods, especially when working with small samples, which positively affects the overall performance of the adaptive algorithm. The accuracy of the estimations is directly correlated with the performance of the detection algorithm, which is confirmed by the results shown in the Figure 15, which demonstrate the detection characteristics of (9) for different approaches to the estimation of interferences.




a) b)

Figure 15: Detection characteristics of the adaptive detector, using different methods of estimating parameters (MLM (LMS), Yule-Walker, Levinson-Durbin), and sample sizes: a) $N = 64$; b) $N = 128. F = 0.01$.

According to the results of the detection characteristics (Figure 15), it can be stated that with the increase in the sample size, the detection efficiency for different evaluation algorithms tends to coincide. However, for practically significant sample sizes $N = 64, 128$, the maximum likelihood method (MLM) demonstrates higher estimation accuracy compared to the classic Yule-Walker and Levinson-Durbin procedures. This is because MLM provides a more efficient use of sample information, especially in the case of a small amount of data, which is confirmed by faster convergence and lower systematic error compared to classical methods.

## 5. Conclusions

In this work, an analysis of the effectiveness of synthesized adaptive algorithms for the detection of radar signals against the background of broadband interference was carried out.

Algorithms (7, 8, 9, 10) are synthesized using a statistical approach that includes a statistical model of interference and takes into account the a priori uncertainty in the parameters of both the interference model and the signal. An important feature of such algorithms is the structure of the evaluation of interference parameters, which characterizes their ability to dynamically adapt to changes in the statistical properties of interference, which allows them to reduce the level of false alarms and increase the accuracy of detecting target signals in complex interference conditions.

The simulation results show (Figure 7, 10, 13 and 14) that the synthesized algorithms demonstrate the effectiveness of signal detection in complex broadband interference conditions, which is ensured by evaluating and adjusting filters to the interference parameters. The obtained results of computer simulation confirmed that the MLM method provides more accurate parameter estimates, especially for small samples, which is critically important for real radar systems. This makes it possible to increase the accuracy and reliability of adaptive algorithms in conditions of intense and dynamic disturbances.

It should be noted that an increase in the sample size has a positive effect on the overall detection efficiency, however, for practically significant sample values ($N = 16; 32; 64; 128$), adaptive algorithms using the MLM method demonstrate significantly higher signal detection accuracy, which is confirmed by the results of computer modeling.

Thus, the conducted study demonstrates that the proposed adaptive detection algorithms based on autoregressive models can be effectively applied to increase the accuracy of signal detection in complex conditions, especially in conditions of dynamically changing obstacles.

## References


[1] M. A. Richards, J. A. Scheer, W. A. Holm, Principles of Modern Radar: Basic Principles, SciTech Publishing, Southampton, 2013.

[2] I. Prokopenko, I. Omelchuk, Y. Chyrka, RADAR signal parameters estimation in the MTD tasks, International Journal of Electronics and Telecommunications 58(2) (2012) 159–164. doi: 10.2478/v10177-012-0023-5.

[3] D. I. Lekhovytskiy, V. P. Ryabukha, G. A. Zhuga, D. S. Rachkov, A. V. Semeniaka, MTD in pulse radars: 5. Adaptive systems for interperiod processing of Gaussian signals against the background of Gaussian clutter, Applied Radio Electronics: Scientific Journal 10(4) (2011) 508–525.

[4] D. I. Lekhovytskiy, To the theory of adaptive signal processing in systems with centrally symmetric receive channels, EURASIP Journal on Advances in Signal Processing 2016(33) (2016). doi: 10.1186/s13634-016-0329-z.

[5] M. Malanowski, Comparison of adaptive methods for clutter removal in PCL radar, in: Proceedings of International Radar Symposium, IEEE, Krakow, Poland, 2006, pp. 1–4.

[6] S. M. Kay, Fundamentals of Statistical Signal Processing: Volume II Detection Theory, Prentice-Hall, New Jersey, 1998.

[7] J. Neyman, E. S. Pearson, On the problem of the most efficient test of statistical hypotheses, Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character 231 (1933) 289–337.

[8] S. J. Orfanidis, Optimum Signal Processing: An Introduction. Second Edition, Collier Macmillan, London, 1988.

[9] J. Xue, S. Xu, J. Liu, M. Pan, J. Fang, Bayesian detection for radar targets in compound-gaussian sea clutter, IEEE Geoscience and Remote Sensing Letters 19 (2022): 4020805. doi: 10.1109/LGRS.2022.3140727.

[10] H. L. Van Trees, Detection, Estimation, and Modulation Theory: Detection, Estimation, and Linear Modulation Theory, Wiley, New York, 2001.

[11] B. Farhang-Boroujeny, Adaptive Filters: Theory and Applications, Wiley, New York, 1999.

[12] O. Solomentsev, M. Zaliskyi, O. Zuiev, Estimation of quality parameters in the radio flight support operational system, Aviation 20(3) (2016) 123–128. doi: 10.3846/16487788.2016.1227541.

[13] E. J. Kelly, An adaptive detection algorithm, IEEE Transactions on Aerospace and Electronic Systems AES-22(2) (1986) 115–127. doi: 10.1109/TAES.1986.310745.

[14] B. Widrow, S. D. Stearns, Adaptive Signal Processing, Prentice-Hall, Englewood Cliffs, 1985.

[15] S. Haykin, Adaptive Filter Theory, Prentice Hall, Upper Saddle River, NJ, 4th edition, 2002.

[16] I. G. Prokopenko, A. Yu Dmytruk, Implementation of adaptive algorithms in the task of MTDI filtration, in: Proceedings of International Conference on Information and Telecommunication Technologies and Radio Electronics, IEEE, Odesa, Ukraine, 2021, pp. 226-231, doi: 10.1109/UkrMiCo52950.2021.9716711.

[17] I. G. Prokopenko, A. S. Savchenko, K. I. Prokopenko, A. Yu. Dmytruk, Efficiency of using neural networks in the problem of signal detection, Science-based Technologies 2 (2024) 126–135. doi: 10.18372/2310-5461.62.18706.

[18] I. Prokopenko, K. Prokopenko, A. Dmytruk, Application of neural network technologies in signal detection tasks, in: Proceedings of International Conference on Information and Telecommunication Technologies and Radio Electronics (UkrMiCo), IEEE, Kyiv, Ukraine, 2023, pp. 151–156. doi: 10.1109/UkrMiCo61577.2023.10380364.

[19] I. Prokopenko, K. Prokopenko, A. Dmytruk, Comparison of neural network and statistical approaches to the problem of signal detection. in: I. Ostroumov, M. Zaliskyi (Eds.), Proceedings of the 2nd International Workshop on Advances in Civil Aviation Systems Development. ACASD 2024, volume 992 of Lecture Notes in Networks and Systems, Springer, Cham, 2024, pp. 224–241. doi: 10.1007/978-3-031-60196-5_18.

[20] Y. D. Shirman, et al., Radio Electronic Systems: Fundamentals of Construction and Theory (Reference book), 1998.
[21] A. di Vito, M. Naldi, Robustness of the likelihood ratio detector for moderately fluctuating radar targets, IEE Proceedings - Radar, Sonar and Navigation, 146(2) (1999) 107–122. doi: 10.1049/ip-rsn:19990261.
[22] G. E. Box, G. M. Jenkins, Time Series Analysis: Forecasting and Control, 3rd Edition, Prentice Hall, Englewood Cliffs, 1994.
[23] D. I. Lekhovytskyi, I. G. Kirillov, Modeling of passive interference by pulse radars based on arbitrary order autoregressive processes. Information Processing Systems 3 (2008) 90–101.