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ANALYSIS OF THE EFFECTIVENESS OF ALGORITHMS FOR ESTIMATING PARAMETERS OF AUTOREGRESSIVE MODELS IN THE PROBLEM OF SIGNAL DETECTION IN INTERFERENCE CONDITIONS

Introduction

In contemporary radar systems, the challenge of detecting signals amidst complex interference remains pertinent. Systems designed for moving target detection (MTD) frequently face various forms of interference that impair their effectiveness. These disturbances may include both Gaussian and non-Gaussian types, such as those following Laplace or K distributions, common in dynamic environments or scenarios involving electronic warfare (EW) measures. In such conditions, traditional signal processing methods may prove to be ineffective, requiring the development of more sophisticated approaches to signal detection [1]. Thus, the use of adaptive detection algorithms capable of adjusting their parameters according to the characteristics of the interference is of particular interest [2, 3, 4].

Accordingly, one of the important stages of the synthesis of such algorithms is the mathematical modeling of obstacles. One of the effective modeling strategies is the use of autoregressive (AR) models, which are widely used to represent random processes and allow the determination of the statistical structure of interferences [5, 6, 7].

It is worth noting that the use of these models largely depends on the accuracy of their parameter estimation, which directly affects the quality of interference compensation.

Analysis of recent research and publications

A sufficient number of efficient algorithms are synthesized to estimate the parameters of autoregressive models used in various fields of science, including signal processing, econometrics, meteorology, and medical research [8, 9].

For example, the work [10, 11] examines classical parameter estimation methods, such as the Yule-Walker method, widely used in spectral signal analysis. This method provides stable estimates for steady-state processes but has certain limitations in the presence of non-stationary disturbances.

The work [12] extended this concept by using adaptive algorithms, such as Recursive Least Squares (RLS), which ensure constant updating of AR model parameters. These algorithms can be useful for applications in systems with a dynamic interference environment, as they can adjust estimates in the face of changing interference statistics. Another approach to parameter estimation in complex conditions is presented in the paper [13], where a noise-resistant method for estimating the parameters of AR models in the frequency domain is proposed, which is based on the expectation–maximization (EM) algorithm.

All studies emphasize the importance of accurate estimation of the parameters of autoregressive models to ensure effective background interference compensation. Although there is a considerable amount of work that examines different approaches to estimating the parameters of AR models, the key focus of this research is to analyze existing algorithms for estimating the parameters of AR models such as the Yule-Walker equation, the Levinson-Durbin algorithm, the maximum likelihood method (MLE), and an algorithm such as Recursive Least Squares (RLS) which are traditional and quite widespread.

The purpose of the article

This work aims to compare the effectiveness of algorithms for estimating the parameters of autoregressive (AR) models in the context of signal detection under interference conditions for enhancing detection performance in practical applications.

Theoretical background

Autoregressive (AR) models have found wide use in time series analysis and signal processing because they can serve as a convenient tool for understanding and forecasting data. The main idea of AR models is their ability to 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 a sum of its previous values with a given random generating process, which in turn allows for the effective mathematical representation of various types of interference.

Mathematically, the AR model of order p can be described by the following equation (1):

$$x_i = \sum_{j=1}^{p} a_j\, x_{i-j} + \varepsilon_i, \qquad (1)$$

where x_i – signal counts at the current time i, a_j – are the autoregressive coefficients, ε_i – generating random process.

It is worth noting that on the basis of model (1), the structure of the notch filter is formed, which in the general detection system is designed to compensate for interference. Since in real detection systems, we cannot have a priori information about the statistical distribution of interference, the filter parameters must be estimated.

Thus, this feature can be used in adaptive filtering, which is the basis of adaptive detection algorithms, according to which the parameters of the generation process are estimated, which allows you to adjust the filter parameters taking into account changes in the statistical characteristics of the input signal for further compensation for interference.

Algorithms for estimating parameters of autoregressive models

The estimation of the parameters of the autoregressive process is an integral part of the structure of the adaptive detection algorithm, since in the work of AR models serve as a mathematical basis for the formalization of interference. The estimation procedure consists in determining the parameters (coefficients) of the AR(p) model, which describes the dependence of the current value of the process on the previous ones, and allows you to evaluate changes in the characteristics of the interference.

The Yule-Walker method is one of the most common approaches to estimating the parameters of autoregressive processes AR(p), which is formed by estimating the autocorrelation function [6]. This method is based on using the Yule-Walker system of equations, which allows estimating the coefficients of the autoregressive model by solving a system of linear equations obtained from the autocorrelation properties of a stationary process (2):

$$\begin{bmatrix} r_{xx}[0] & r_{xx}[-1] & \cdots & r_{xx}[1-p] \\ r_{xx}[1] & r_{xx}[0] & & r_{xx}[2-p] \\ \vdots & & \ddots & \vdots \\ r_{xx}[p-1] & r_{xx}[p-2] & \cdots & r_{xx}[0] \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} r_{xx}[1] \\ r_{xx}[2] \\ \vdots \\ r_{xx}[p] \end{bmatrix}, \qquad (2)$$

where $r_{xx}[q] = \sum_{j=1}^{p} a_j r_{xx}[q-j]$ – autocorrelation value.

The resulting system of equations (2) can be solved using known methods for solving SLAR, for example, the matrix method or the Gaussian method, obtaining estimates of the coefficients $a_1, \ldots, a_p$. For the 2nd-order autoregressive model AR (2), which is widely used for modeling complex interference situations, the system (2) will have the form (3):

$$\underbrace{\begin{bmatrix} r_{xx}[0] & r_{xx}[-1] \\ r_{xx}[1] & r_{xx}[0] \end{bmatrix}}_{R} \times \underbrace{\begin{bmatrix} a_1 \\ a_2 \end{bmatrix}}_{A} = \underbrace{\begin{bmatrix} r_{xx}[1] \\ r_{xx}[2] \end{bmatrix}}_{E} \qquad (3)$$

Using the matrix method, the solution to the system can be written as $A = R^{-1}E$.

The matrix of autocorrelation coefficients (2), under the condition of stationary of the random process, is Toeplitz, that is, one where each diagonal element remains unchanged along the entire diagonal.

This feature allows for the effective use of the Levinson-Durbin recursive method, which is an iterative algorithm used to solve systems of Yule-Walker equations when estimating the coefficients of the autoregressive model AR(p).

In the general case, the Levinson-Durbin algorithm can be formalized as follows. In the first step, the initial conditions are set, namely the value of the AR (1) model parameter and the initial value of the error in determining the parameters ε_0 and ε_1 (4).

$$\varepsilon_0 = r_{xx}[0];\ a_1 = \frac{r_{xx}[1]}{r_{xx}[0]} = k_1;$$
$$\varepsilon_1 = (r_{xx}[0] - |r_{xx}[1]|^2)/r_{xx}[0], \qquad (4)$$

where a_1 is the AR(1) parameter, k_1 is the reflection coefficient.

At each iteration step (p), which corresponds to the order of the model, taking into account (4), a recursive calculation of the parameters of the AR(p) model is performed. At each stage, the reflection coefficients k_p are determined, which characterize the degree of interaction between the current value of the process and its previous values. The calculated coefficients k_p are used to update the previous values of the model parameters a_j at the current calculation step (p) and calculate the current value of the parameter a_p at the step (p) (5).

$$k_p = \frac{r_{xx}[p] - \sum_{j=1}^{p-1} a_j^{(p-1)} r_{xx}[p-j]}{\varepsilon_{p-1}};$$
$$a_p^{(p)} = k_p;\ a_j^{(p)} = a_j^{(p-1)} - k_p a_{p-j}^{(p-1)}; \quad (5)$$
$$j = \overline{1, p-1};$$
$$\varepsilon_p = (r_{xx}[0] - |k_p{}^2|)\varepsilon_{p-1}.$$

Another method for estimating the parameters of an autoregressive (AR) process, particularly suitable for nonstationary environments, is the Recursive Least Squares (RLS) algorithm.

The goal is to recursively estimate a minimizing the weighted prediction error. The RLS algorithm, adapted for this task, operates as follows (6):

$$d_n = \frac{P_{n-1} x_{n-1}}{\lambda + x^T{}_{n-1} P_{n-1} x_{n-1}};$$
$$e_n = x_n - a^T{}_{n-1} x_{n-1};$$
$$P_n = \frac{1}{\lambda}\,[P_{n-1} - \ d_n x^T{}_{n-1} P_{n-1}]; \quad (6)$$
$$a_n = a_{n-1} + d_n e_n,$$

where a_n – is the estimate of AR parameters; P_n – is the inverse correlation matrix; $\lambda \in [0,1]$ –is the forgetting factor (selected based on the expected stationary of the signal: values close to 1 (λ = 0.99) are used for nearly stationary processes, while smaller values (λ = 0.95) enable faster adaptation to time-varying dynamics); d_n – is the gain vector; e_n – is the a priori prediction error.

However, under conditions where the assumptions of stationary of random processes or sufficient sample size may not be met, one of the methods that is expediently used in such cases is the maximum likelihood method [15].

The general principle of MLM is to find such values of model parameters for which the observed data are most likely. In the general case, finding estimates of unknown parameters of a random process when applying MLM is based on maximizing the likelihood function, which, under the condition of a fixed sample implementation, is described by the multivariate density distribution of the process (7):

$$L(x_1, \dots, x_n | \theta_1, \dots, \theta_l) = \prod_{i=1}^{n} f(x_1, \dots, x_n | \theta_1, \dots, \theta_l) \quad (7)$$

In order to obtain the maximum of function (7), partial derivatives are calculated with respect to unknown parameters and set equal to zero, as a result of which a system of equations is formed for finding parameter estimates (8).

$$\begin{cases} \frac{\partial L(x_1, \dots, x_n | \theta_1, \dots, \theta_l)}{\partial \theta_1} = 0 \\ \vdots \\ \frac{\partial L(x_1, \dots, x_n | \theta_1, \dots, \theta_l)}{\partial \theta_l} = 0 \end{cases} \quad (8)$$

It is worth noting that, provided that the interference is described by a Gaussian probability distribution, the parameter estimates obtained by the maximum likelihood method will coincide with the estimates obtained by the least squares method (LSM).

Unlike Gaussian processes, where the MML and least squares estimates coincide, in the case of non-Gaussian distributions, the likelihood function is formed based on a more complex structure of the interference clutter distribution, which complicates the application of standard estimation methods. In the case of non-Gaussian interference, such as a process with a Laplace or K-distribution, the likelihood function may have a nonlinear form, so maximizing this function requires adapting the IMF or using more specialized numerical methods, such as the Newton-Raphson method or variations of gradient algorithms.

Computer simulation

Analysis of the effectiveness of algorithms for estimating autoregressive parameters is an important stage of the study since the use of effective algorithms ensures an increase in the accuracy of estimating the parameters of autoregressive models, thereby ensuring high-quality rejection of noise components.

Within the framework of computer modeling, the study is divided into two stages: at the first stage, the effectiveness of algorithms for estimating the parameters of the autoregressive clutter model is analyzed, taking into account fundamental statistical indicators, in particular, the mathematical expectation and the standard deviation; at the second, using the synthesized structure of the adaptive detector, the influence of the obtained estimates on the detection characteristics.

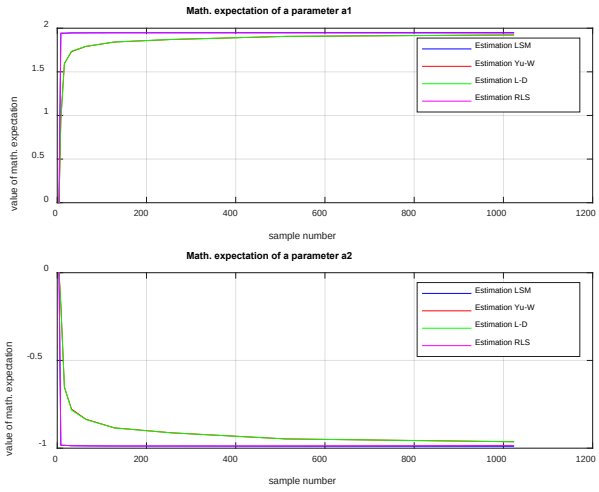

Fig. 1. Mathematical expectation of the estimates of the parameters of the Gaussian autoregressive noise model a1 and a2 (true values a = [1.95; -0.99])

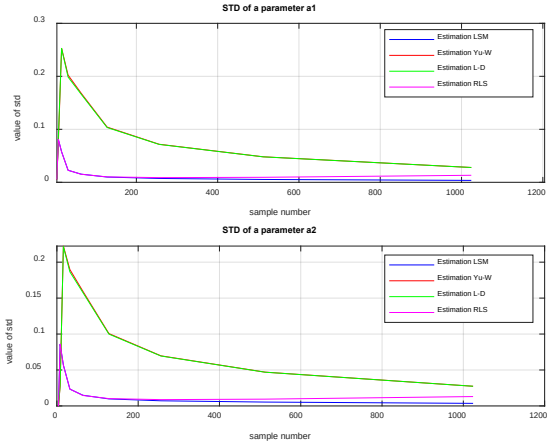

Fig. 2. Standard deviation of the estimates of the parameters of the Gaussian autoregressive noise model a1 and a2 (true values a = [1.95; -0.99])

The simulation results shown in Fig. 1 and Fig. 2 demonstrate that the estimates of the parameters of the autoregressive process obtained using the estimation algorithms based on the maximum likelihood method, which in the case of the Gaussian autoregressive model, the noise can be implemented by the least squares method (LSM) and the recurrent least squares method, compared to the traditional Yule-Walker and Levinson-Durbin methods, are closer to the true ones.

The estimates obtained using the LSM (blue lines), under the specified conditions, are reasonable and asymptotically unbiased, in turn, the estimates obtained using the RLS (pink lines) also demonstrate similar results, however, the values of the LSM begin to increase with increasing sample size, which may be due to the numerical instability of the covariance matrix update, high correlation of the input data, lack of regularization or an excessively large value of the forgetting coefficient.

Unlike the Yule-Walker and Levinson-Durbin methods (red and green lines), which demonstrate reduced accuracy on small samples, the LMS and RLS methods provide better convergence of estimates even with a limited amount of data N = [16; 32; 64; 128], which is especially important for practical systems operating in real-time. It is also worth noting that the obtained parameter estimates affect the signal detection efficiency.

This is confirmed by the analysis of the detection characteristics shown in Fig. 3.40, which demonstrates the dependence of the probability of correct detection on the accuracy of the parameter estimation algorithms.

Fig. 3 illustrates the detection characteristics of the adaptive algorithm [16] for detecting a harmonic signal against the background of a Gaussian autoregressive interference model when using different parameter estimation methods.

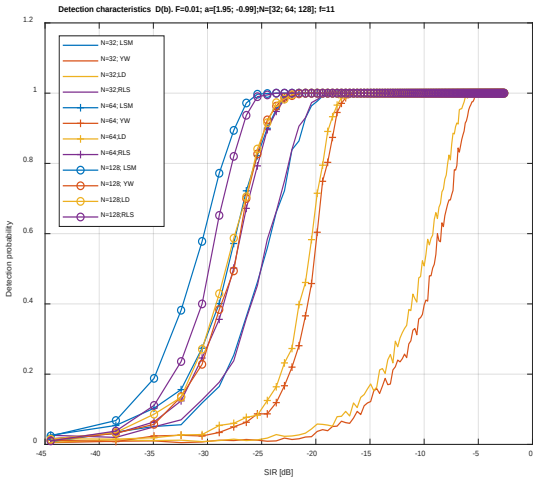

Fig. 3. Detection characteristics of the adaptive harmonic signal detection algorithm against the background of a Gaussian autoregressive interference model when using different parameter estimation methods (LMS, Yule-Walker equation (YW), Levinson-Durbin method (LD), RLS) and sample size N = [32; 64; 128]

The obtained detection characteristics (Fig. 3) demonstrate that with an increase in the sample size, the detection efficiency when using the specified estimation algorithms begins to converge, however, at practically significant volumes N = [32, 64, 128], the accuracy of estimates using the LSM and RLS algorithms is significantly higher than when using the classical Yule-Walker and Levinson-Durbin estimation algorithms.

The gain in detection efficiency (threshold signal at D = 0.9) is significant and reaches up to 15 dB at N = 32, and up to 3 dB at N = 128.

It is worth noting that at a sample size of N = 32, the detection characteristic where estimates using the RLS algorithm are used demonstrates better results, but with an increase in the sample size, the results are better demonstrated by estimates using the LSM algorithm.

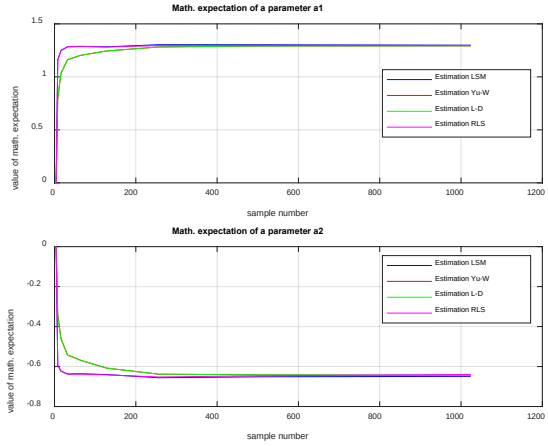

Fig. 4. Mathematical expectation of the estimates of the parameters of the Gaussian autoregressive noise model a1 and a2 (true values a = [1.3; -0.65])

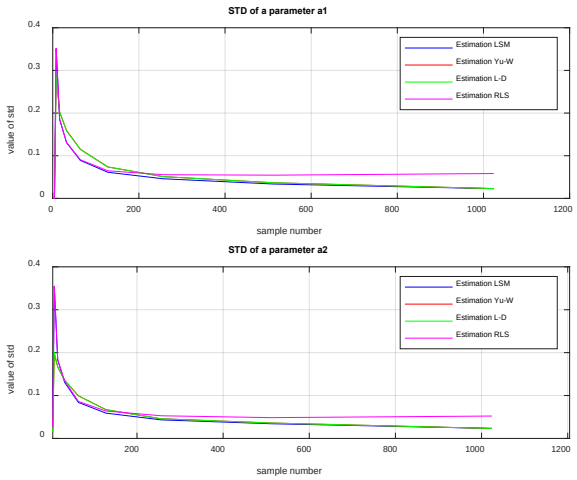

Fig. 5. Standard deviation of the estimates of the parameters of the Gaussian autoregressive noise model a1 and a2 (true values a = [1.3; -0.65])

It is also worth noting that the spectral composition of the interference also significantly affects the quality of estimates obtained using different algorithms (Fig. 4, Fig. 5).

This is manifested in the conditions of broadband low-frequency interference. In such cases, the use of an estimation algorithm based on the maximum likelihood method (MLM) does not demonstrate a fundamental advantage over classical algorithms such as the Yule-Walker and Levinson-Durbin methods.

This effect remains stable even if the signal spectrum is located near the maximum of the interference spectrum. Under these conditions, the detection characteristics for all considered estimation algorithms become almost identical (Fig. 6).

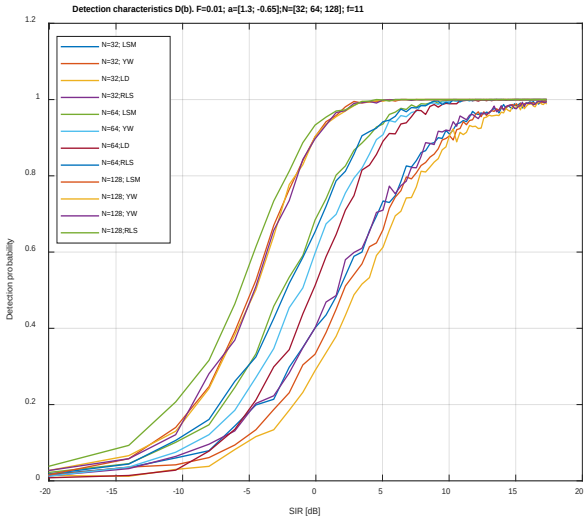

Fig. 6. Detection characteristics of the adaptive harmonic signal detection algorithm against the background of a broadband low-frequency Gaussian autoregressive interference clutter model when using different parameter estimation methods

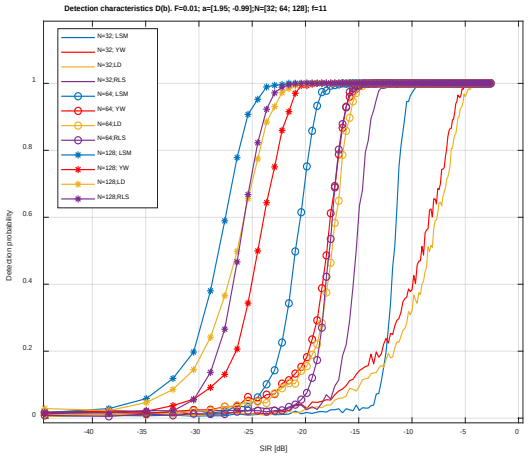

Fig. 7. Detection characteristics of the adaptive harmonic signal detection algorithm on the background Gaussian autoregressive interference model when impulse interference occurs, $p = 0.01$

At the same time, the impact of the appearance of impulse interference also manifests itself differently on the estimation algorithms under the influence of different bands of the main interference, so under the influence of narrow-band powerful interference, an increase in the probability of the appearance of an impulse leads to a deterioration in the detection characteristics of the algorithm, at the same time, the impact of the used parameter estimation algorithms will be correlated with the results presented in Fig. 3, i.e., the algorithms LMS and RLS will be more resistant to the appearance of impulse interference than LD and YW.

The gain in detection efficiency (threshold signal at $D = 0.9$) is significant and reaches up to 6 dB at $N = 32$, and up to 3 dB at $N = 128$.

Considering the problem of synthesizing an algorithm for estimating the parameters of a non-Gaussian autoregressive interference model, it is necessary to emphasize the importance of ensuring the robustness of the obtained estimates. Robustness allows for maintaining high accuracy and stability of estimates even under conditions of significant deviations of the statistical properties of interference from the Gaussian model.

The analysis of the results of modeling aimed at assessing the effectiveness of the use of such algorithms confirms the feasibility of their application under conditions of non-Gaussian interference.

In particular, the modeling results demonstrated that the algorithm developed based on the LMS method maintains a low level of bias and stability of the variance of estimates (Fig. 8, Fig. 9), even under difficult conditions of narrow-band powerful interference and the presence of the influence of impulse components.

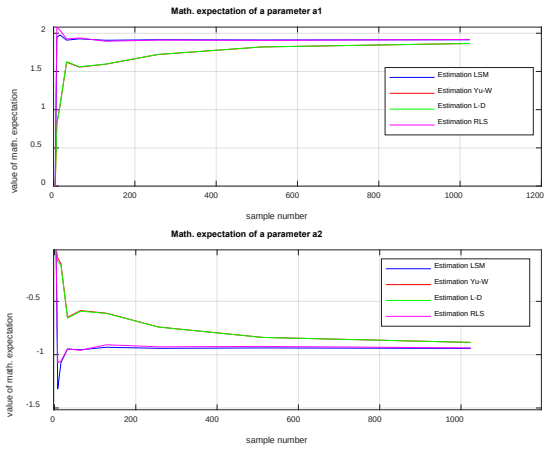

Fig. 8. Mathematical expectation of the estimates of the parameters of the nonGaussian (Laplace) autoregressive noise model a1 and a2 (true values a = [1.9; -0.95])

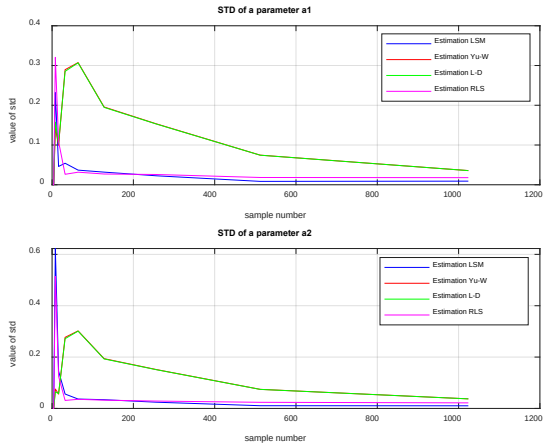

Fig. 9. Standard deviation of the estimates of the parameters of the nonGaussian (Laplace) autoregressive noise model a1 and a2 (true values a = [1.9; -0.95]).

It is also worth noting that in the presence of non-Gaussian noise, the influence of parameter estimates may manifest itself differently. Since the proposed estimation algorithm is based on the maximum likelihood method, it allows taking into account the statistical characteristics of the interference, which, in turn, ensures the robustness of the obtained estimates. At the same time, estimates obtained using the recursive least squares method also demonstrate resistance to the action of such noise.

The obtained detection characteristics (Fig. 10, Fig. 11) also demonstrate that with increasing sample size, the detection efficiency when using the specified estimation algorithms improves. However, at practically significant volumes N = [32, 64, 128], the accuracy of estimates by the OLS and RLS algorithms will be better than when using the classical Yule-Walker and Levinson-Durbin estimation algorithms. The gain in detection efficiency (threshold signal at D = 0.9) is significant and reaches up to 5 dB.

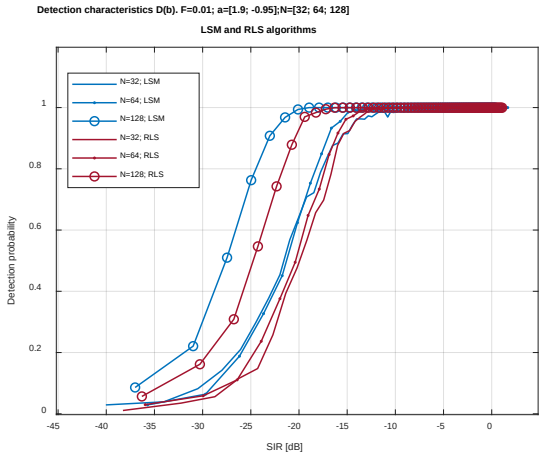

Fig. 10. Detection characteristics of the adaptive detection algorithm against the background of a nonGaussian autoregressive interference model, parameter estimation methods (LMS, RLS), N = [32; 64; 128]

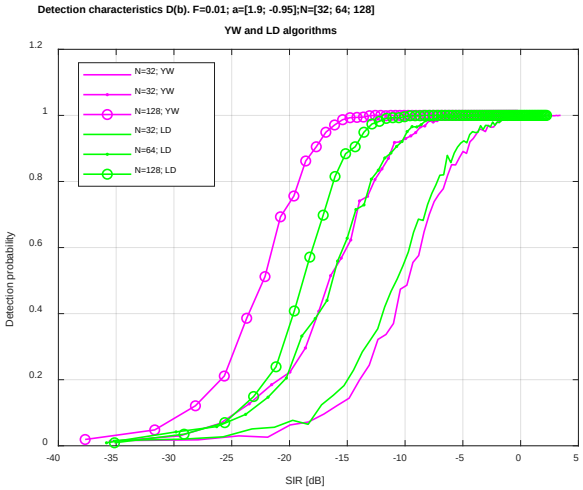

Fig. 11. Detection characteristics of the adaptive detection algorithm against the background of a nonGaussian autoregressive interference model, parameter estimation methods (Yule-Walker equation (YW), Levinson-Durbin method (LD)), N = [32; 64; 128]

Conclusions

The article studies the effectiveness of autoregressive model parameter estimation algorithms in the context of improving the quality of adaptive signal detection in an interference environment. The relevance of this problem is due to the need to increase the probability of correct detection in a non-stationary statistical environment, typical for the operation of modern radio-electronic systems. In this context, the paper provides a comparative analysis of several parameter estimation algorithms: the Yule-Walker, Levinson–Durbin methods, the maximum likelihood method, which corresponds to the least squares method (LSM), and the recursive least squares method (RLS).

The results of computer modeling confirm that the use of parameter estimation methods, such as the least squares method (LSM) and the recursive least squares method (RLS), allows you to obtain estimates that are on average closer to the true values compared to the classical Yule-Walker and Levinson-Durbin methods. In particular, the estimates obtained by the Least Squares method demonstrate better convergence and asymptotic unbiasedness (Fig. 1, Fig. 2).

It is demonstrated that the accuracy of estimating the parameters of the autoregressive model significantly affects the characteristics of the adaptive detector since errors in the estimates can lead to a deterioration in the selective properties of the filter and a decrease in the probability of detection. Thus, the problems of estimating the parameters of the AR model cannot be considered separately from the detection problem and must be integrated into the general system of adaptive signal processing.

The computer modeling performed allowed us to compare the practical effectiveness of classical and modern approaches to estimating AR parameters, in particular the Yule-Walker, Levinson-Durbin, least squares (LS) methods, and recursive LMS (RLS).

The gain in detection efficiency (threshold signal at $D = 0.9$) is significant and reaches up to 15 dB at $N = 32$, and up to 3 dB at $N = 128$. It is noted that for small samples ($N = 32$) the RLS algorithm demonstrates better results; however, with an increase in the sample size, the estimates obtained by the least squares method turn out to be more accurate and stable. At the same time, a characteristic feature of the recursive method was revealed – with an increase in the number of processed samples, an increase in the mean square deviation of the estimates is noted, which is probably due to the accumulation of numerical errors in matrix calculations, and requires the introduction of regularization tools or modified versions of the algorithm.

Special attention is paid to the influence of the spectral composition of the interference on the behavior of the estimation algorithms. It is demonstrated that in a broadband low-frequency interference environment, the use of LMS and PLS algorithms does not provide significant advantages over classical methods. This emphasizes the importance of taking into account the spectral features of interference when choosing an algorithm for estimating AR model parameters in real-time systems**.**

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АНАЛІЗ ЕФЕКТИВНОСТІ АЛГОРИТМІВ ОЦІНЮВАННЯ ПАРАМЕТРІВ АВТОРЕГРЕСІЙНИХ МОДЕЛЕЙ В ЗАДАЧІ ВИЯВЛЕННЯ СИГНАЛІВ В УМОВАХ ЗАВАД

Підвищення точності ймовірності правильного виявлення в умовах дії завад залишається актуальною задачею, особливо в середовищі із динамічними та нестаціонарними перешкодами. У цьому контексті зростає інтерес до використання адаптивних алгоритмів виявлення, здатних змінювати свої параметри відповідно до статистичних характеристик завадового тла.

Одним із ключових аспектів синтезу таких алгоритмів є адекватне моделювання перешкод. Авторегресійні моделі дозволяють ефективно моделювати завади, використовуючи залежність між попередніми значеннями сигналів, що важливо для оптимальної компенсації перешкод.

Ефективність побудови таких моделей значною мірою залежить від точності оцінки їх параметрів, що безпосередньо впливає на якість адаптивної компенсації перешкод і, відповідно впливає на характеристики виявлення загального алгоритму. Тому в цій статті досліджуються алгоритми оцінки параметрів АР-моделей – зокрема методи максимальної правдоподібності, рекурсивні та класичні підходи Юла–Вокера та Левінсона–Дурбіна.

Також увагу приділено дослідженню впливу обраного алгоритму оцінювання на точність апроксимації статистичних характеристик завадового тла, а також на подальшу ефективність адаптивного виявлення сигналів. Для цього реалізовано двоетапне комп'ютерне моделювання: на першому етапі здійснено порівняльний аналіз точності оцінок параметрів АР-моделі; на другому – оцінено вплив отриманих оцінок на ймовірнісні характеристики адаптивного виявлення в умовах завад.

Ключові слова: адаптивні алгоритми, авторегресійна модель, оцінка параметрів, компенсація перешкод, виявлення сигналів, обробка даних.

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ANALYSIS OF THE EFFECTIVENESS OF ALGORITHMS FOR ESTIMATING PARAMETERS OF AUTOREGRESSIVE MODELS IN THE PROBLEM OF SIGNAL DETECTION IN INTERFERENCE CONDITIONS

Improving the accuracy of the probability of correct detection under interference conditions remains a pressing task, especially in an environment with dynamic and non-stationary interference. In this context, there is growing interest in using adaptive detection algorithms that can change their parameters following the statistical characteristics of the background noise. One of the key aspects of the synthesis of such algorithms is adequate modeling of interference. Autoregressive models allow for effective modeling of interference using the dependence between the previous values of signals, which is important for optimal interference compensation.

The effectiveness of building such models largely depends on the accuracy of estimating their parameters, which directly affects the quality of adaptive interference compensation and, accordingly, the detection characteristics of the general algorithm. Therefore, this article investigates the algorithms for estimating the parameters of AR models - in particular, maximum likelihood methods, recursive and classical Yule-Walker, and Levinson–Durbin approaches.

Attention is also paid to studying the impact of the selected estimation algorithm on the accuracy of approximation of the statistical characteristics of the noise background, as well as on the subsequent effectiveness of adaptive signal detection. For this purpose, a two-stage computer simulation was implemented: at the first stage, a comparative analysis of the accuracy of estimates of the parameters of the AR model was carried out; at the second stage, the impact of the obtained estimates on the probabilistic characteristics of adaptive detection in interference conditions was assessed.

Keywords: adaptive algorithms, autoregressive model, parameter estimation, clutter compensation, clutter, signal detection, data processing.

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