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Oleksandr Laptiev
Dr. Sci. (Technical), Senior Researcher
Associate Professor Department of Cyber Security and Information Protection
Taras Shevchenko National University of Kyiv, Kyiv, Ukraine
ORCID: 0000-0002-4194-402X
alaptev64@ukr.net

Yuliia Khokhlachova
Candidate of Technical Sciences, Professor,
Professor of the Department of Software Engineering and Cybersecurity
State University of Trade and Economics, Kyiv, Ukraine
ORCID: 0000-0002-0787-5112
Y.Khokhlachova@knute.edu.ua

Tetiana Laptieva
PhD in Cybersecurity,
Associate Professor Department of Cyber Security
National Technical University «Kharkiv Polytechnic Institute», Kharkiv, Ukraine
ORCID: 0000-0002-5223-9078
tetiana1986@ukr.net

Vadym Stetsenko
PhD student of Cyber Security Department
National Technical University "Kharkiv polytechnic institute", Kharkiv, Ukraine
ORCID: 0009-0008-5315-5539
4all2dream@gmail.com

Serhii Laptiev
PhD in Cybersecurity
State University «Kyiv aviation institute» , Kyiv, Ukraine
ORCID: 0000-0002-7291-1829
salaptiev@gmail.com

METHOD FOR DETECTING DANGEROUS DIGITAL RADIO SIGNALS

Abstract. Detection and recognition of digital radio signals remains a critical challenge, particularly in electromagnetically contested environments. This study examines low-pass filtering approaches characterized by either linear or quadratic dependence of the output on the input signal amplitude. These filters operate by coherently summing deterministic signal components while incoherently accumulating random noise contributions resulting in constructive reinforcement of the signal energy and sublinear growth of noise power, which substantially enhances the signal-to-noise ratio (SNR). A rectangular pulse, serving as a representative model of modern digital communication waveforms, was applied to both linear and quadratic filter architectures. A comprehensive statistical characterization including mathematical expectation, variance, root mean square deviation, correlation coefficient, and SNR was performed in both time and frequency domains for input and output signals. To enable objective evaluation of filtering performance, a novel efficacy metric referred to as the payoff coefficient was introduced to quantify improvements in detection reliability. Further simulations analyzed the envelope voltage at the output of an ideal bandpass filter when excited by rectangular pulses of varying durations, emulating signals typical of low-probability-of-intercept (LPI) communication systems. Transient responses and spectral leakage were examined under diverse signal-noise correlation conditions.

The findings confirm that covert signals can be reliably extracted using two-dimensional likelihood density estimation, which effectively discriminates interfering components from the composite received waveform. At the system level, incorporating narrowband low-frequency filtering into the signal processing pipeline improved the noise immunity of airborne digital radio signal detection and recognition by 23%. This enhancement significantly strengthens operational resilience in hostile electromagnetic environments, with direct relevance to secure communications, electronic warfare, and signals intelligence applications.

Keywords: covert signal detection, quadratic filtering, noise immunity, digital radio signal, low-pass filtering, coherent summation, signal-to-noise ratio (SNR), covert communication, likelihood density estimation.

INTRODUCTION

Radio interference refers to any electrical oscillations that, when entering a radio receiver or emanating from it, hinder the accurate identification of the desired radio signal. When both the signal and interference act simultaneously at the receiver input, they produce a random oscillatory process at the output, making it difficult to precisely determine the signal's parameters. Reliable signal detection is possible only when the signal-to-interference power ratio at the receiver output exceeds a certain threshold. The minimum signal strength that still ensures satisfactory detection depends on the interference level and defines the receiver's sensitivity.

The ability of a radio receiver to maintain a required signal quality in the presence of interference is known as noise immunity (or interference resilience). Enhancing this property represents one of the most critical and challenging problems in radio engineering. Addressing it effectively requires thorough analysis of interference characteristics, understanding their impact mechanisms on signal integrity, and developing methods to mitigate their adverse effects.

In the context of digital radio signals, interference poses specific challenges during signal detection and recognition. Therefore, noise immunity is a central consideration in the study of these processes.

Analysis of recent publications and problem statement. A significant body of research has addressed the topic of noise immunity in radio systems. For instance, reference [1] examines technical approaches aimed at enhancing radio performance through improved noise immunity. It explores various methods for boosting interference resistance and analyzes the key factors influencing it. The study identifies relay-type interferences as particularly detrimental, specifically, those for which the correlation between the useful signal and the interference is significantly higher than that observed with pseudo-random sequence noise or harmonic interference. The work also demonstrates that different source coding schemes do not substantially alter the robustness of radio stations when subjected to such interferences. However, it does not consider scenarios involving the detection of probabilistic digital signals.

References [2,3] investigate the noise immunity of a standard detection chain comprising three sequential components: an ideal bandpass filter, a quadratic detector, and an ideal integrator. The probabilistic detection framework developed in these studies can be extended to other practically relevant receiver architectures. Nevertheless, the specific impact of interference on rectangular-shaped signals, commonly used to model digital waveforms, is not examined.

In works [4,5], statistical radio engineering methods are employed to evaluate the noise immunity of quadrature amplitude modulated (QAM) signals under combined noise and harmonic interference. Analytical relationships are derived for bit error probability as functions of signal-to-noise ratio, interference power, and the spectral offset of the interfering tone relative to the center frequency of the desired signal. The results indicate that harmonic interference severely degrades QAM reception, with the degradation worsening as the modulation order (i.e., signal "positionality") increases. Despite these insights, the actual detection and recognition of digital radio signals remain outside the scope of the analysis.

References [6–8] present an optimization model for power measurement in electronic circuits, developed using MATLAB-based simulations. The proposed algorithms are adaptable for characterizing a wide range of information-carrying signals, including modern digital waveforms. Meanwhile, [9–12] propose a method for coordinating data exchange among mobile technical platforms operating in intense electromagnetic environments.

A review of current literature reveals a notable gap: the unique challenges of noise immunity in the context of detecting and recognizing digital signals used in digital radio broadcasting have received little attention. Consequently, there is a clear need for dedicated research into noise immunity within automated systems designed for the detection and identification of digital radio broadcasts.

Presentation of main material

Most noise-immunity techniques rely on the fundamental principle of distinguishing the desired signal from interference through averaging. This approach exploits the fact that, during summation, the useful signal accumulates coherently, due to its consistent phase and structure, whereas noise components add incoherently and tend to cancel out over time. To implement this averaging, two main types of linear filtering systems are commonly employed: narrowband (bandpass) filters and low-pass filters. Both can be optimized, either by adjusting bandwidth, shape, or other parameters, to enhance signal integrity and suppress unwanted interference.

When analyzing interference suppression, it is often assumed that the narrowband filter introduces no distortion to the signal passing through it. In theoretical treatments, such a filter is modeled as an ideal bandpass filter, characterized by a specific amplitude-frequency response profile:

$$K(\omega)=\begin{cases}1 \quad якщо \quad \omega_0-\dfrac{\Delta\omega}{2}\le|\omega|\le\omega_0+\dfrac{\Delta\omega}{2}\\[2ex] 0 \quad якщо \quad \left]-\infty,\omega_0-\dfrac{\Delta\omega}{2}\right[\;U\;\left]\omega_0+\dfrac{\Delta\omega}{2},\infty\right[\end{cases}, \tag{1}$$

where $\Delta\omega$ – filter bandwidth.

For an ideal filter, an effective band $\Delta\ \omega_e$ and band $0,707-\Delta\ \omega_{\sqrt{2}}$, is equal to the filter transparency band $\Delta\omega$.

For filters, the assumption is that $\Delta\ \omega\ <<\Delta\ \omega_0$.

The frequency response of the expression for (1) is the impulse transition characteristic, which will be determined by the expression:

$$h_\delta(t)=\frac{\Delta\omega}{\pi}\cdot\frac{\sin\dfrac{\Delta\omega t}{2}}{\dfrac{\Delta\omega t}{2}}\cos\omega_0 t\ . \tag{2}$$

Given that the digital signal is not a clear pulse [10], it is possible to calculate the envelope voltage at the output of an ideal filter when exposed to a rectangular pulse of duration:

$$x(t)=\begin{cases}X_m\cos\omega_0 t \quad якщо \quad 0\le t\le T\\ 0 \quad якщо \quad]-\infty,0[\;U\;]T,\infty[\end{cases}, \tag{3}$$

where X_m – the envelope signal $x(t)$ at the inlet of the filter.

Using the envelope voltage theorem of the narrowband filter, we write the expression for the envelope voltage at the output of the filter:

$$Y_m(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} K_{fn}(j\omega) S_{X_m}(j\omega) e^{j\omega t} dt \,, \quad (4)$$

where $S_{X_m}(j\omega) = \int_{-\infty}^{\infty} X_m e^{-j\omega t} dt$ – the amplitude spectrum of the envelope signal $x(t)$,

K_{fn} – complex factor of low frequency filter transmission:

$$K_{fn}(j\omega) = \begin{cases} 1 \quad якщо \quad -\frac{\Delta\omega}{2} \le |\omega| \le \frac{\Delta\omega}{2} \\ 0 \quad якщо \quad \left]-\infty, \frac{\Delta\omega}{2}\right[\; U \; \left]\frac{\Delta\omega}{2}, \infty\right[\end{cases} \quad (5)$$

Substituting expression (5) into expression (4), we get the expression:

$$Y_m(t) = \frac{X_m}{2\pi}\left(Si(\Delta\omega t) - Si(\Delta\omega(t-T))\right), \quad (6)$$

where $Si(z) = \int_0^z \frac{\sin t}{t} dt$ – integral sinus [11].

In Fig. 1 dependency graphs of the duration of the influencing rectangular pulse (blue color - pulse duration T = 1, red color - T = 10, green color - T = 15 and black color - T = 20) on the frequency range (filter bandwidth).

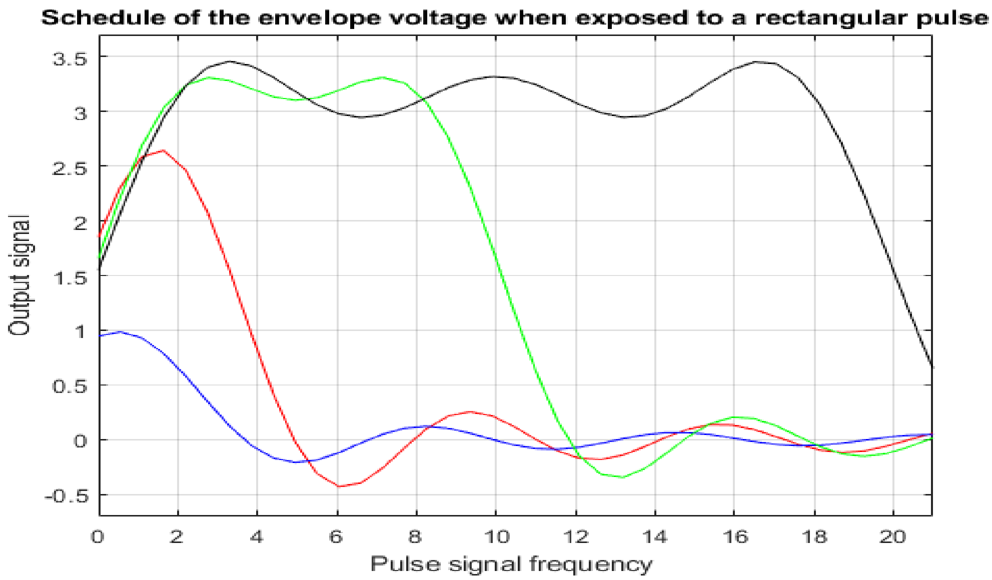

Fig. 1. Graph of the envelope voltage when exposed to a rectangular pulse signal

The graphical results reveal pronounced discrepancies between the input rectangular pulse and the corresponding output waveform. Notably, the extent of pulse distortion escalates with increasing pulse duration. This degradation in pulse fidelity can be quantified by the ratio of the envelope duration at the filter output to that of the original input pulse envelope.

These observations suggest that brief rectangular pulses can be effectively isolated through the use of a bandpass filter [12].

To proceed with the characterization of the interference component, the autocorrelation coefficient of white noise after it has passed through the bandpass filter is computed:

$$R_w(\tau)=\frac{\int\limits_0^\infty K^2(\omega)\cos\omega t dt}{\int\limits_0^\infty K^2(\omega)d\omega}. \qquad (7)$$

After substituting expression (1) into expression (7) we obtain:

$$R_w(\tau)=\frac{1}{\Delta\omega}\int\limits_{\omega_0-\frac{\Delta\omega}{2}}^{\omega_0+\frac{\Delta\omega}{2}}\cos\omega\tau d\omega=\frac{\sin\left(\omega_0+\frac{\Delta\omega}{2}\right)\cdot\tau-\sin\left(\omega_0-\frac{\Delta\omega}{2}\right)\cdot\tau}{\Delta\omega\tau} \qquad (8)$$

or
$$R_w(\tau)=r_w(\tau)\cos\omega_0\tau, \qquad (9)$$

where $r_w(\tau)=\dfrac{\sin(\Delta\omega\frac{\tau}{2})}{\Delta\omega\frac{\tau}{2}}$ – the envelope of the autocorrelation coefficient of the process at the output of the bandpass filter.

Due to the fact that the signal of digital means of silent retrieval of information is a signal of a rectangular pulse, with an envelope of duration *T*, the expression has the form [13]:

$$y_s=\begin{cases}A\cos(\omega_0+\varphi_0) & ,0\le t\le T\\ 0 &]-\infty,t[U]t,\infty[\end{cases}. \qquad (10)$$

Then the numerical characteristics of the quadratic filter filtering process will look like:

$$m_1[z_{\Sigma 0}(t)]=\begin{cases}A_1\sigma_{yN}^2(1+q^2), & 0\le t\le T\\ A_1\sigma_{yN}^2=m_1[z_{N0}(t)], &]-\infty,t[U]t,\infty[\end{cases}, \qquad (11)$$

where $m_1[z_{0N}(t)]$ – mathematical expectation of low-frequency noise fluctuation.

$$R_{z\Sigma 0}(t,t+\tau)=\begin{cases}\dfrac{r_{yN}^2(\tau)+2q^2r_{yN}(\tau)}{1+2q^2}=R_{z\Sigma 0}(\tau), & 0\le t\le(T-\tau)\\ r_{yN}^2(\tau)=R_{zN0}(\tau), &]-\infty,t[U]t,\infty[\end{cases} \qquad (12)$$

$R_{zN0}(\tau)$ – autocorrelation coefficient of low-frequency noise interference.

$$D_{z\Sigma N}=\sigma_{z\Sigma N}^2(t)=\begin{cases}A_1^2\sigma_{yN}^4(1+2q^2)=\sigma_{z\Sigma 0}^2, & 0\le t\le T\\ A_1^2\sigma_{yN}^4=\sigma_{zN0}^2, &]-\infty,t[U]t,\infty[\end{cases} \qquad (13)$$

A stochastic process is termed quasi-stationary if its mean (mathematical expectation) and autocorrelation function remain invariant under time shifts, provided the time separation between observations is held constant. Under this condition, the process at the filter output—comprising the superposition of signal and interference—retains its quasi-stationary character, as the additive combination does not alter this property [14].

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For a linear filter, the key quantitative characteristics of the filtering process are expressed as follows:

$$m_1[z_{\Sigma 0}(t)] = \frac{A_1\sigma^2_{y\Sigma}}{\sqrt{2\pi}}; \quad (14)$$

$$R_{z\Sigma 0}(\tau) \approx r^2_{yN}(\tau); \quad (15)$$

$$\sigma^2_{z\Sigma 0} = \frac{A_1\sigma^2_{y\Sigma}}{8\pi}, \quad (16)$$

where $\sigma^2_{y\Sigma} = D_{y\Sigma}$ – the variance of the total process at the inlet of the filter. It is determined by:

$$\sigma^2_{y\Sigma} = \sigma^2_{yS} + \sigma^2_{yN}, \quad (17)$$

where $D_{ys} = \sigma^2_{ys}, D{=}_{ys}\sigma^2_{yN}$ – signal dispersion and interference at the filter input.

We calculate the mutual correlation functions $z_{N0}(t)$, $z_{\Sigma 0}(t)$ of the output signals.

In the case of an interference signal, the mathematical expectation for a second order mixed signal $z_N(t)$, $z_\Sigma(t)$ will be determined by the expression:

$$m_1[z_N(t_1), z_\Sigma(t_2)] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} z_N(t_1) z_\Sigma(t_2) w_2[y_N(t_1), y_\Sigma(t_2)]\times$$
$$\times dy_N(t_1)dy_\Sigma(t_2) = A_2^2\int_0^{\infty}\int_0^{\infty} y_N(t_1)y_\Sigma(t_2)w_2[y_N(t_1), y_\Sigma(t_2)]\times, \quad (18)$$
$$\times dy_N(t_1)dy_\Sigma(t_2)$$

where $w_2[z_N(t_1), z_\Sigma(t_2)]$ – two-dimensional probability density of stationary normal processes $y_N(t)$, $y_\Sigma(t)$. Given that the autocorrelation coefficient of both signals is the same and equal to $R_{yN}(\tau)$, it is possible to write an expression for $w_2[z_N(t_1), z_\Sigma(t_2)]$ – two-dimensional probability density in the form:

$$w_2[z_N(t_1), z_\Sigma(t_2)] = \frac{1}{2\pi\ \sigma_{yN}\sigma_{y\Sigma}\sqrt{1-R^2_{yN}(\tau)}}\cdot\exp\times$$
$$\times\left(-\frac{1}{2(1-R^2_{yN}(\tau)}[\frac{y^2_N(t_1)}{\sigma^2_{yN}} - 2R_{yN}(\tau)\frac{y_N(t_1)y_\Sigma(t_2)}{\sigma_{yN}\sigma_{y\Sigma}} + \frac{y^2_\Sigma(t_1)}{\sigma^2_{y\Sigma}}\right). \quad (19)$$

Performing the substitution of the form: $\frac{y_N(t_1)}{\sigma_{yN}} = x$, $\frac{y_N(t_2)}{\sigma_{y\Sigma}} = y$ we get the expression:

$$.\ m_1[z_N(t_1), z_\Sigma(t_2)] = \frac{A_2\sigma_{yN}\sigma_{y\Sigma}}{2\pi\ \sqrt{1-R^2_{yN}(\tau)}}\cdot\int_0^{\infty}\int_0^{\infty}\exp\left(-\frac{x^2-2R_{yN}(\tau)xy+y^2}{2(1-R^2_{yN}(\tau))}\right)dxdy. \quad (20)$$

To assess how the correlation coefficient—interpreted here in terms of signal-to-noise ratio—

affects the mathematical expectation (i.e., to examine the influence of noise relative to the signal), a numerical simulation of the process will be carried out.

In correlation theory, the strength of a relationship is commonly classified using Cheddock's scale, a well-established benchmark in statistical analysis: a correlation is considered weak when its magnitude ranges from 0.1 to 0.3; moderate from 0.3 to 0.5; noticeable from 0.5 to 0.7; high from 0.7 to 0.9; and very high (or strong) from 0.9 to 1.0.

Accordingly, for the purposes of this study, correlation coefficient values corresponding to weak, moderate, and high levels of association are systematically selected, as outlined in [15].

The outcomes of the simulation are presented in Figures 2 and 3:

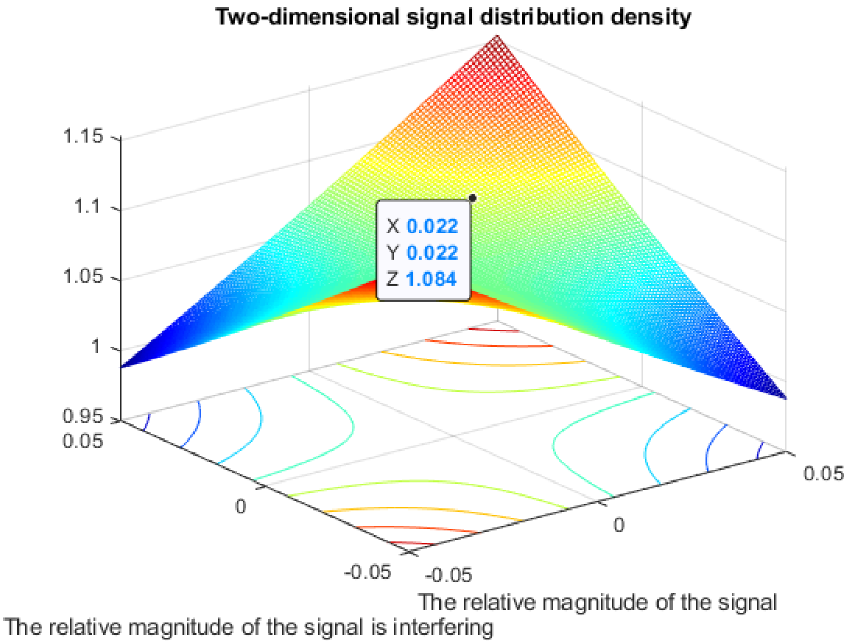

Fig. 2. Two-dimensional density of signal distribution at R_{yN} *= 0.3 (moderate dependence)*

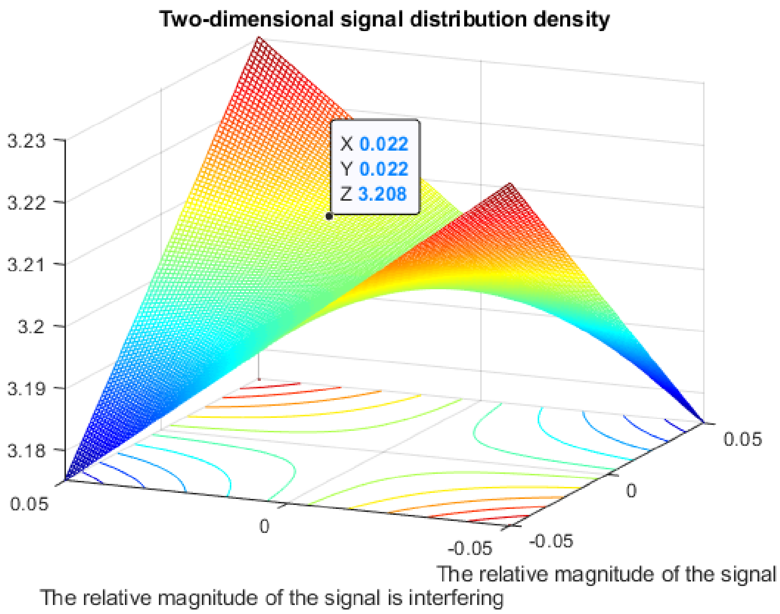

Fig. 3. Two-dimensional density of signal distribution at R_{yN} *= 0.9 (moderate dependence)*

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To facilitate the analysis of the obtained results, a reference point with identical coordinates—corresponding to the same relative levels of signal and interference—was selected on each of the presented graphs.

As evident from Figures 2 and 3, the probability density magnitude of the signal progressively increases as the correlation strength rises from weak to high. This trend demonstrates an enhanced capability to discriminate between the desired signal and interfering components, attributable to the noise suppression achieved through filtering.

To compute the signal-to-noise ratio at the output of a conventional detection chain, under the influence of an additive noise component *n*(*t*) and a signal component *s*(*t*) applied at its input, the following expression is used:

$$x(t) = S(t) + N(t). \quad (21)$$

Suppose that the signal and the interference are stationary white noise, with zero mathematical expectation $m_1(S(t)) = m_1(N(t)) = 0$. Signal and interference are uncorrelated: $m_1(S(t)(N(t)) = 0$ and defined over a long period of time. Then it is possible to write the expressions:

$$D_\Sigma = \sigma_\Sigma^2 = \Delta f_e S_\Sigma; \; D_s = \sigma_s^2 = \Delta f_e S_s; \; D_N = \sigma_N^2 = \Delta f_e S_N, \quad (22)$$

where Δf_e – effective filter transparency band;

$D_\Sigma = \sigma_\Sigma^2$ – variance and root mean square deviation of the signal mixture;

$D_s = \sigma_s^2$ – dispersion and root mean square deviation of the signal;

$D_N = \sigma_N^2$ – dispersion and standard deviation of interference;

$S_\Sigma; S_s; S_N$ – spectral densities, respectively, of a mixture of signal and noise, signal and noise.

The assumptions we have made are as follows:

$$\sigma_\Sigma^2 = \sigma_s^2 + \sigma_N^2 \text{ or } D_\Sigma = D_S + D_N. \quad (23)$$

The low-frequency component of the voltage at the output of the tract, detected at the time of reference $t = T$, denote $u_{\Sigma 0}$, the interference voltage u_{N0}, the voltage sum of the signal $u_{\Sigma 0}$. It should be noted that u_{N0} and $u_{\Sigma 0}$ are random variables.

The appearance of a signal at the input of the tract, detected at time $t = T$, can change the mathematical expectation of the low-frequency component voltage at the output of the tract, from magnitude $m_1[u_{N0}(t)]$ to $m_1[u_{\Sigma 0}(t)]$. This signal increase is called a useful signal. Write for him the expression:

$$C = m_1[u_{\Sigma 0}(T)] - m_1[u_{N0}(T)] = \Delta\, m_1[u_0(T)]. \quad (24)$$

In such a case, the interference at the same instant of time T will be determined by the mean square value of fluctuation of the random probable magnitude:

$$N = \sigma_{u\Sigma}(T) = \left(m_1\left[u_{\Sigma 0}{}^2\,(T)\right] - m_1{}^2\left[u_{\Sigma 0}(T)\right]\right)^{\frac{1}{2}}. \quad (25)$$

The signal / interference ratio for $t = T$ will be:

$$\frac{C}{N} = \frac{m_1[u_{\Sigma 0}(T)] - m_1[u_{N0}(T)]}{\left(m_1\left[u_{\Sigma 0}{}^2\,(T)\right] - m_1{}^2\left[u_{\Sigma 0}(T)\right]\right)^{\frac{1}{2}}}. \quad (26)$$

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Expressions (17 - 19) are the definition of signal, interference and signal / interference ratio at the output of the receiving path. In the future, our task will be to determine the signal, interference and their correlation through the corresponding parameters at the input of the receiving path.

There are two methods for determining this relationship: spectral and temporal.

In the time method, the voltage at the output of the receiving path at time $t = T$ will be determined by the expression:

$$u(T) = \int_0^T h_\delta(T - t) z(t) dt , \tag{27}$$

where h_δ – impulse transient response of the filter, $z(t)$ – input voltage.

The mathematical expectation of this voltage when exposed to the input of a mixture of signal and interference will be:

$$m_1\left[u_\Sigma(T)\right] = \int_0^T h_\delta(T - t) m_1\left[z_\Sigma(t)\right] dt . \tag{28}$$

Due to the fact that z_Σ – is a stationary process, its mathematical expectation is independent of time, then we have:

$$m_1\left[u_\Sigma(T)\right] = m_1\left[z_\Sigma(t)\right] \int_0^T h_\delta(T - t) dt = m_1\left[z_\Sigma(t)\right] \int_0^T h_\delta(t) dt . \tag{29}$$

Similarly, it is possible to determine mathematical expectation when exposed only to interference:

$$m_1\left[u_N(T)\right] = m_1\left[z_N(t)\right] \int_0^T h_\delta(t) dt . \tag{30}$$

Substituting expressions (18) and (19) into expression (13) we obtain:

$$C = \Delta\ m_1\left[z_0(T)\right] \int_0^T h_\delta(t) dt , \tag{31}$$

where $\Delta\ m_1\left[z_0(t)\right] = m_1\left[u_{\Sigma 0}(t)\right] - m_1\left[u_{N0}(t)\right]$ increasing the mathematical expectation of the low-frequency component voltage at the output of the filter.

The dispersion of the fluctuations at the output of the low-pass filter is determined by:

$$D_{u\Sigma} = \sigma^2_{u\Sigma} = \left(m_1\left[u_\Sigma{}^2\ (T)\right] - m_1{}^2\ \left[u_\Sigma(T)\right] \right) . \tag{32}$$

From the expression:

$$u^2_\Sigma(T) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_\delta(T - t_1, T) h_\delta(T - t_2, T) z_\Sigma(t_1) z_\Sigma(t_2) dt_1 dt_2 \tag{33}$$

we have:

$$m_1[u^2_\Sigma(T)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_\delta(T - t_1, T) h_\delta(T - t_2, T) m_1[z_\Sigma(t_1) z_\Sigma(t_2)] dt_1 dt_2 ; \tag{34}$$

$$D_{u\Sigma}=\sigma_{u\Sigma}^{2}(T)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}h_{\delta}(T-t_1,T)h_{\delta}(T-t_2,T)\times$$
$$\times m_1[z_{\Sigma}(t_1)z_{\Sigma}(t_2)]dt_1dt_2-m_1^2[z_{\Sigma}(t)]\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}h_{\delta}(T-t_1,T)h_{\delta}(T-t_2,T)\times$$
$$\times h_{\delta}(T-t_2,T)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}h_{\delta}(T-t_1,T)h_{\delta}(T-t_2,T)\times$$
$$\times m_1[z_{\Sigma}(t_1)z_{\Sigma}(t_2)]dt_1dt_2-m_1^2[z_{\Sigma}(t)]dt_1dt_2 \tag{35}$$

We will replace: $\tau=t_2-t;\ \ d\tau=dt_2;\ \ t=t_2;\ \ dt=dt_1$ Then we will have:

$$D_{u\Sigma}=\sigma_{u\Sigma}^{2}=\sigma_{z\Sigma}^{2}[\int_{-\infty}^{\infty}Q_h(\tau,T)R_{z\Sigma}(\tau)d\tau], \tag{36}$$

where
$$Q_h(\tau,T)=\int_{-\infty}^{\infty}h_{\delta}(T-t\ ,T)h_{\delta}(T-t-\tau,T)dt\ ; \tag{37}$$

$$R_z(\tau)=\frac{m_1\big[z_{\Sigma}(t)z_{\Sigma}(t+\tau)\big]-m_1{}^2\ \big[z_{\Sigma}(t)\big]}{\sigma_{z\Sigma}^2}, \tag{38}$$

where $R_{z\Sigma}(\tau)$ – autocorrelation coefficient, $D_{z\Sigma}=\sigma_{z\Sigma}^{2}$ – the variance of the process when exposed to the input of the sum of signal and interference.

Assume that according to expression (37) the interference: $N=\sigma_{u\Sigma}(T)$ then we will have:

$$N=\sigma_{u\Sigma}(T)=\sigma_{\Sigma 0}[\int_{-\infty}^{\infty}Q_h(\tau,T)R_{z\Sigma}(\tau)d\tau]^{\frac{1}{2}}. \tag{39}$$

Due to the fact that energy spectrum is the main factor in determining the signal of the means of silent receiving of information , we will find the expression for interference in spectral form.

To do this, we use the Wiener-Hinchin theorem, which establishes the relationship between the correlation function and the power spectral density $g(\omega)$:

$$K(\tau)=\int_{-\infty}^{\infty}g(\omega)e^{j\omega t}d\omega. \tag{40}$$

Then we get:

$$N=\left(\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}h_{\delta}(T-t,T)h_{\delta}(T-t-\tau,T)dt\times[\int_{-\infty}^{\infty}g_{z\Sigma 0}(\omega)e^{j\omega\tau}d\omega]d\tau\right)^{\frac{1}{2}}=$$
$$=\left(\int_{-\infty}^{\infty}g_{z\Sigma 0}(\omega)d\omega\int_{-\infty}^{\infty}h_{\delta}(T-t,T)dt\int_{-\infty}^{\infty}h_{\delta}(T-t-\tau,T)e^{j\omega\tau}d\tau\right)^{\frac{1}{2}}=$$
$$=\left(\int_{-\infty}^{\infty}g_{z\Sigma 0}(\omega)K_T(j\omega)d\omega\int_{-\infty}^{\infty}h_{\delta}(T-t,T)e^{j\omega(T-\tau)}dt\right)^{\frac{1}{2}}=$$
$$=\left(\int_{-\infty}^{\infty}g_{z\Sigma 0}(\omega)\left|K_T(j\omega)\right|^2d\omega\right)^{\frac{1}{2}}=\left(\int_{-\infty}^{\infty}G_{z\Sigma 0}(\omega)\left|K_T(j\omega)\right|^2d\omega\right)^{\frac{1}{2}} \tag{41}$$

where $K_T(j\omega)$ – low frequency filter complex frequency response;

$g_{z\Sigma 0}(\omega)$ – spectral power density of low-frequency fluctuations at the output of the filter over the entire frequency axis.

$$G_{z\Sigma 0}(\omega)=\begin{cases}2g_{z\Sigma 0}(\omega)=\dfrac{2\sigma^2_{z\Sigma 0}}{\pi}\int\limits_0^{\infty} R_{z\Sigma 0}(\tau)\cos\omega\tau d\tau, & \omega>0\\ 0, & \omega<0\end{cases}, \quad (42)$$

where $G_{z\Sigma 0}(\omega)$ – the spectral power density of the signal $z_{\Sigma 0}(t)$, determined only in the region of positive frequencies.

Thus, the expression for the signal-to-noise ratio at the output of a typical radio path in the mode of detecting a signal against the background of the signal takes the form:

Temporarily:

$$\frac{C}{N}=\frac{\Delta\ m_1[z_0(t)]\int\limits_0^T h_\delta(t)dt}{\sigma_{\Sigma 0}[\int\limits_{-\infty}^{\infty} Q_h(\tau,T)R_{z\Sigma 0}(\tau)d\tau]^{\frac{1}{2}}}. \quad (43)$$

Spectral recording form:

$$\frac{C}{N}=\frac{\Delta\ m_1[z_0(t)]K_T(0)}{[\int\limits_{-\infty}^{\infty} G_{z\Sigma 0}(\omega)\left|K_T(j\omega)\right|^2 d\omega]^{\frac{1}{2}}}. \quad (44)$$

In addition to the signal-to-noise ratio, the filter's characteristic is the winning ratio, which is determined by the expression:

$$K_B=\frac{C/N вих}{C/N вх}. \quad (45)$$

Substituting expression (43) into expression (45), we obtain:

$$K_B=[\frac{\Delta\ m_1[u_0(T)]}{\sigma_{u\Sigma 0}(T)}]/[\frac{\Delta\ m_1[z_0(T)]}{\sigma_{z\Sigma 0}(T)}]=[\frac{\Delta\ m_1[u_0(T)]}{\Delta\ m_1[z_0(T)]}]/[\frac{\sigma_{u\Sigma 0}(T)}{\sigma_{z\Sigma 0}(T)}], \quad (46)$$

where $\frac{\Delta\ m_1[u_0(T)]}{\Delta\ m_1[z_0(T)]}]$, $[\frac{\sigma_{u\Sigma 0}(T)}{\sigma_{z\Sigma 0}(T)}]$ – determine the increase in mathematical expectation and the average square deviation of low-frequency fluctuations as a result of processing the input signal by a low-pass filter.

Consequently, enhancing the noise immunity of the detection and recognition system necessitates the incorporation of a low-pass filter. Such a filter effectively suppresses or entirely removes low-frequency interference components from the analysis.

An examination of current trends in the evolution of covert information acquisition technologies reveals a clear shift toward operational frequencies in the high-frequency domain. Specifically, the carrier of the information signal is increasingly migrated to higher frequency bands, where the tasks of detecting and recognizing digital signals become notably more complex.

By excluding low-frequency interference from consideration, through appropriate filtering, the overall noise immunity of the system is substantially improved.

CONCLUSIONS

The present study investigates the specific characteristics and efficacy of employing low-pass filters to enhance the noise immunity of an automated system designed for the detection and recognition of digital radio broadcasts. It is demonstrated that the underlying operational principle of such filters relies on a summation mechanism: the desired (useful) signal components accumulate coherently due to their deterministic phase and amplitude structure, whereas noise contributions, being stochastic and uncorrelated, add incoherently, thereby diminishing in relative magnitude through the averaging effect inherent in the filtering process. As a result, the signal-to-noise ratio improves, facilitating more reliable signal extraction.

Given the distinct temporal and spectral properties of modern digital waveforms, particularly those employed in covert or passive information-gathering systems, the key statistical descriptors of the processed signal are rigorously defined. These include the mathematical expectation, variance, standard deviation, and correlation coefficient. Furthermore, both linear and quadratic filter responses are analytically and numerically evaluated under the influence of an input rectangular pulse, which serves as a representative model for digital signals used in silent (non-emitting or low-probability-of-intercept) communication technologies.

Simulations were conducted to obtain the envelope voltage waveforms at the output of an ideal bandpass filter when excited by rectangular pulses of varying durations. Additionally, the filtering process was examined across a range of correlation coefficients, reflecting different degrees of signal–interference dependence. The results confirm that digital signal discrimination is feasible through the estimation of the two-dimensional probability density function of the signal in the presence of interference, against the backdrop of the composite received waveform.

Crucially, quantitative analysis demonstrates that integrating low-frequency filters with appropriately constrained bandwidth into the signal processing chain yields a measurable improvement in system robustness. Specifically, the noise immunity of the digital radio signal detection and recognition system is enhanced by approximately 23%, thereby significantly increasing its reliability in electromagnetically dense or adversarial environments. This finding underscores the practical value of tailored low-pass filtering strategies in modern digital signal intelligence and monitoring applications.

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Лаптєв Олександр Анатолійович
доктор технічних наук, старший науковий співробітник
доцент кафедри кібербезпеки та захисту інформації
Київський національний університет імені Тараса Шевченка, Київ, Україна
ORCID: 0000-0002-4194-402X
olaptiev@knu.ua

Хохлачова Юлія Євгеніївна
кандидат технічних наук, професор
професор кафедри інженерії програмного забезпечення та кібербезпеки
Державний торговельно-економічний університет, Київ, Україна
ORCID: 0000-0002-0787-5112
Y.Khokhlachova@knute.edu.ua

Лаптєва Тетяна Олександрівна
доктор філософії з кібербезпеки та захисту інформації
доцент кафедри кібербезпеки,
НТУ "Харківський політехнічний інститут", Харків, Україна
ORCID: 0000-0002-5223-9078
tetiana1986@ukr.net

Стеценко Вадим Олегович
здобувач ступеню доктор філософії кафедри кібербезпеки
НТУ "Харківський політехнічний інститут", Харків, Україна
ORCID: 0009-0008-5315-5539
4all2dream@gmail.com

Лаптєв Сергій Олександрович
доктор філософії з кібербезпеки та захисту інформації
Державний університет «Київський авіаційний інститут», Київ, Україна
ORCID: 0000-0002-7291-1829
salaptiev@gmail.com

МЕТОД ВИЯВЛЕННЯ НЕБЕЗПЕЧНИХ ЦИФРОВИХ РАДІОСИГНАЛІВ

Анотація. Виявлення та розпізнавання цифрових радіосигналів залишається однією з ключових науково-технічних задач, особливо в умовах електромагнітної конкуренції. У роботі досліджуються методи низькочастотної фільтрації, у яких вихідна величина залежить від амплітуди вхідного сигналу лінійно або квадратично. Такі фільтри ґрунтуються на когерентному (фазоузгодженому) підсумовуванні детермінованих компонентів корисного сигналу та некогерентному накопиченні випадкових шумових складових, що забезпечує конструктивне посилення енергії сигналу за умови сублінійного зростання потужності шуму, істотно підвищуючи співвідношення сигнал/шум (С/Ш). Для моделювання сучасних цифрових радіосигналів як вхідний використовувався прямокутний імпульс, який подавався на лінійну та квадратичну фільтрові структури. Було проведено повний статистичний аналіз у часовій та частотній областях, що охоплював обчислення математичного сподівання, дисперсії, середньоквадратичного відхилення, коефіцієнта кореляції та С/Ш для вхідних і вихідних сигналів. З метою об'єктивної оцінки ефективності фільтрації запропоновано новий показник — коефіцієнт корисної дії, який кількісно відображає зростання надійності виявлення. Додатково проаналізовано напругу огинаючої на виході ідеального смугового фільтра при подачі прямокутних імпульсів різної тривалості, що імітують сигнали систем зв'язку із низькою ймовірністю перехоплення (LPI). Досліджено перехідні процеси та ефекти спектрального розтікання за різних рівнів кореляції між сигналом і шумом. Результати підтверджують можливість ефективного виділення прихованих сигналів шляхом застосування двовимірного оцінювання функції правдоподібності, що дозволяє надійно відокремлювати завади від загального сигналу.
На рівні системи впровадження вузькосмугової низькочастотної фільтрації в ланцюг обробки сигналу забезпечило підвищення завадостійкості системи виявлення та розпізнавання повітряних цифрових радіосигналів на 23 %. Це покращення істотно

збільшує стійкість функціонування у ворожих електромагнітних умовах і має пряме застосування в галузях безпеки зв'язку, електронної боротьби та радіорозвідки.

Ключові слова: приховане виявлення сигналів, квадратична фільтрація, завадостійкість, цифровий радіосигнал, низькочастотна фільтрація, когерентне підсумовування, відношення сигнал/шум (SNR), прихований зв'язок, оцінка щільності ймовірності.

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