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ENHANCED APPROACH FOR THE IDENTIFICATION OF HAZARDOUS DIGITAL RADIO EMISSIONS

Abstract. The identification and classification of digital radio emissions constitute a significant technical hurdle, especially within electromagnetically contested sectors. This research investigates low-pass filtering techniques, analyzing architectures where the output exhibits either linear or quadratic dependence on the input amplitude. These filtering mechanisms function by coherently aggregating deterministic signal elements while allowing random noise components to accumulate incoherently. This process leads to constructive amplification of signal energy alongside sublinear noise power growth, thereby markedly improving the signal-to-noise ratio (SNR). A rectangular pulse was utilized as a proxy for contemporary digital communication waveforms across both filter types. A thorough statistical analysis was conducted in both time and frequency domains, evaluating metrics such as variance, mathematical expectation, correlation coefficients, and SNR. To objectively assess filtering efficiency, a new metric termed the "payoff coefficient" was established to measure gains in detection reliability. Simulations further explored envelope voltage responses from an ideal bandpass filter stimulated by rectangular pulses of various durations, mimicking Low-Probability-of-Intercept (LPI) systems. The study confirms that covert signals can be effectively isolated using two-dimensional likelihood density estimation. System-level integration of narrowband low-frequency filtering enhanced the noise immunity of airborne digital signal detection by 23%, bolstering operational resilience in hostile environments relevant to electronic warfare and signals intelligence.

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

INTRODUCTION

Radio interference encompasses any electrical oscillations that disrupt the precise identification of a target radio signal, whether entering or emanating from a receiver. When interference and the desired signal coexist at the receiver input, they generate a stochastic oscillatory process at the output, complicating the accurate determination of signal parameters. Reliable detection is achievable only when the signal-to-interference power ratio at the output surpasses a specific threshold. The minimum signal strength required for satisfactory detection, contingent upon the interference level, defines the receiver's sensitivity.

The capacity of a radio receiver to sustain required signal quality amidst interference is termed noise immunity or interference resilience. Improving this characteristic is a paramount challenge in radio engineering. Effective mitigation requires a deep analysis of interference traits, their mechanisms of impact on signal integrity, and the development of countermeasures. In the realm of digital radio emissions, interference creates distinct obstacles during detection and recognition phases, making noise immunity a focal point of study.

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.

Aim and Objectives of the Study. While existing literature addresses general noise immunity, there is a discernible gap regarding automated systems designed specifically for the detection and identification of digital radio broadcasts. Current methods often overlook the unique statistical properties of probabilistic digital signals in contested environments. Consequently, the primary aim of this article is to develop and validate a specialized filtering method that enhances the noise immunity of automated detection systems. Specifically, this study seeks to:

– Analyze the efficacy of linear and quadratic low-pass filtering architectures in distinguishing deterministic digital signals from stochastic noise;
– Develop a novel efficacy metric (payoff coefficient) to quantify improvements in detection reliability;

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– Evaluate the system's performance under varying signal–noise correlation conditions using rectangular pulse models typical of LPI systems;

– Demonstrate quantifiable improvements in operational resilience for airborne digital signal detection applications.

Part 1: Theoretical Framework of Signal Filtering.

Fundamental Principles of Noise Suppression. Most techniques for enhancing noise immunity rely on averaging to distinguish the target signal from interference. This method leverages the principle that useful signals accumulate coherently due to consistent phase and structure, whereas noise components add incoherently, tending to cancel out over time. To execute this averaging, two primary linear filtering systems are utilized: narrowband (bandpass) filters and low-pass filters. Both can be optimized via bandwidth adjustments or parameter tuning to maximize signal integrity.

In interference suppression analysis, narrowband filters are often assumed to introduce no distortion. For such filters, the effective band is equal to the transparency band, assuming the signal bandwidth is significantly smaller than the carrier frequency. The frequency response dictates the impulse transition characteristic. Given that digital signals are not always distinct pulses, one can calculate the envelope voltage at the output of an ideal filter when subjected to a rectangular pulse of a specific duration. Utilizing the envelope voltage theorem for narrowband filters, the output envelope voltage is expressed through the amplitude spectrum of the input envelope and the complex factor of low-frequency filter transmission.

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:

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

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:

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

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:

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

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:

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

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:

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

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

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

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).

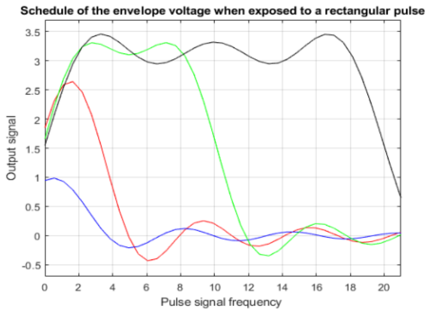

Fig. 1. Graph of the envelope voltage when exposed to a rectangular pulse signal

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:

$$R_w(\tau)=\frac{\int_0^\infty K^2(\omega)\cos\omega t dt}{\int_0^\infty K^2(\omega)d\omega} \tag{7}$$

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

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

or

$$R_w(\tau)=r_w(\tau)\cos\omega_0\tau \tag{9}$$

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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]:

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

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

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

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

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

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

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

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].

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

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

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

$$\sigma^2_{z\Sigma 0}=\frac{A_1\sigma^2_{y\Sigma}}{8\pi} \tag{16}$$

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

$$\sigma^2_{y\Sigma}=\sigma^2_{yS}+\sigma^2_{yN} \tag{17}$$

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:

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

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:

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

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

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

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.

Part 2. Statistical Modeling and Performance Evaluation.

Simulation of Envelope Voltage and Pulse Distortion. Simulations were conducted to visualize the dependency of rectangular pulse duration on frequency range (filter bandwidth). Graphical results indicated significant discrepancies between the input rectangular pulse and the output waveform. Notably, pulse distortion increased with longer pulse durations. This degradation in fidelity is quantified by the ratio of the envelope duration at the filter output versus the original input. These observations suggest that brief rectangular pulses are more effectively isolated using bandpass filters.

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:

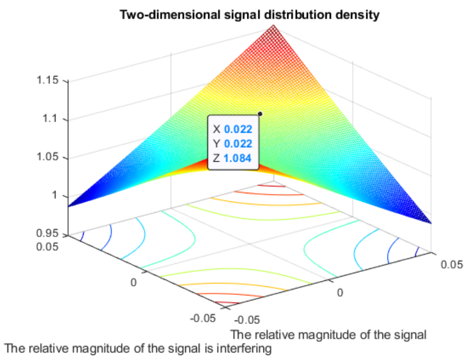

Fig. 2. Two-dimensional density of signal distribution at R_{yN} = 0.3 (moderate dependence)

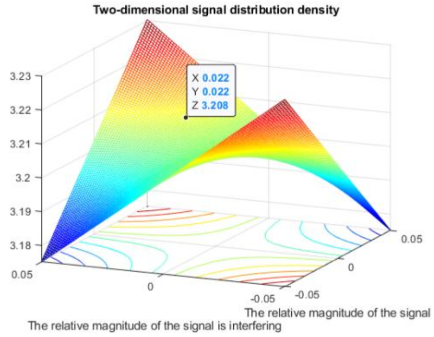

Fig. 3. Two-dimensional density of signal distribution at R_{yN} = 0.9 (moderate dependence)

To facilitate result analysis, a reference point with identical coordinates was selected on distribution graphs representing different correlation strengths. The simulation outcomes revealed that the probability density magnitude of the signal increases progressively as correlation strength rises from weak to high. This trend indicates an enhanced capability to discriminate between the desired signal and interfering components, attributable to noise suppression via filtering. Figures illustrating two-dimensional density at moderate (0.3) and high (0.9) dependence confirm that digital signal discrimination is feasible through the estimation of the two-dimensional probability density function against the composite received waveform.

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:

$$x(t) = S(t) + N(t) \tag{21}$$

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:

$$D_\Sigma = \sigma_\Sigma^2 = \Delta f_e S_\Sigma; \quad D_s = \sigma_s^2 = \Delta f_e S_s; \quad D_N = \sigma_N^2 = \Delta f_e S_N \tag{22}$$

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:

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

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:

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

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:

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

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:

$$u(T) = \int_0^T h_\delta(T-t)z(t)dt \quad (27)$$

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:

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

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

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

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

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

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

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

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:

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

From the expression:

$$u_{\Sigma}^{2}(T)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}h_{\delta}(T-t_1,T)h_{\delta}(T-t_2,T)z_{\Sigma}(t_1)z_{\Sigma}(t_2)dt_1dt_2 \quad (33)$$

we have:

$$m_1[u_{\Sigma}^{2}(T)]=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}h_{\delta}(T-t_1,T)h_{\delta}(T-t_2,T)m_1[z_{\Sigma}(t_1)z_{\Sigma}(t_2)]dt_1dt_2 \quad (34)$$

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

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

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

where

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

$$R_z(\tau)=\frac{m_1\left[z_{\Sigma}(t)z_{\Sigma}(t+\tau)\right]-m_1^{2}\left[z_{\Sigma}(t)\right]}{\sigma_{z\Sigma}^{2}} \quad (38)$$

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:

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

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 $g(\omega)$:

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

Then we get:

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

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:

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

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.

DISCUSSION

The findings of this study highlight the critical role of filtering architecture in modern signal intelligence. The observed 23% improvement in noise immunity through the integration of narrowband low-frequency filtering is significant for several reasons. First, it validates the hypothesis that coherent summation of deterministic signal components outweighs the incoherent accumulation of stochastic noise, particularly in automated detection systems. This aligns with theoretical expectations but provides empirical quantification specific to digital radio broadcasts, a area identified as under-researched in the literature review.

Second, the use of rectangular pulses as models for LPI systems proved effective. The analysis of envelope voltage distortions suggests that while longer pulses suffer more distortion, the statistical properties remain distinct enough for detection via two-dimensional likelihood density estimation. This supports the application of these methods in electronic warfare scenarios where signals are designed to be covert.

Third, the introduction of the "payoff coefficient" offers a standardized metric for future research to compare filtering efficacy objectively. Unlike traditional SNR measurements alone, this coefficient accounts for the reliability growth in detection, providing a more holistic view of system performance.

Comparing these results to prior works (e.g., references [1-5]), which often focus on harmonic interference or specific modulation schemes like QAM, this study broadens the scope to include probabilistic digital signals in automated contexts. The ability to discriminate signals based on correlation strength (weak to high) demonstrates the robustness of the proposed method across varying electromagnetic environments. However, limitations remain regarding the assumption of stationary white noise; future work should explore non-stationary interference models to further validate the approach.

CONCLUSIONS

This study investigated the characteristics and efficacy of low-pass filters in enhancing the noise immunity of automated systems for detecting digital radio broadcasts. The operational principle relies on coherent summation of useful signal components versus incoherent addition of noise, improving the signal-to-noise ratio. Key statistical descriptors, including mathematical expectation, variance, and correlation coefficients, were rigorously defined for modern digital waveforms modeled as rectangular pulses.

Simulations confirmed that digital signal discrimination is feasible through two-dimensional probability density estimation. Crucially, quantitative analysis demonstrated that integrating low-frequency filters with constrained bandwidth into the processing chain enhances the noise immunity of the detection system by approximately 23%. This improvement significantly increases reliability in electromagnetically dense or adversarial environments, underscoring the practical value of tailored low-pass filtering strategies in digital signal intelligence and monitoring applications.

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УДОСКОНАЛЕНИЙ ПІДХІД ДО ІДЕНТИФІКАЦІЇ НЕБЕЗПЕЧНИХ ЦИФРОВИХ РАДІОВИПРОМІНЮВАНЬ

Анотація. Ідентифікація та класифікація цифрових радіовипромінювань становить значну технічну проблему, особливо в електромагнітно-конкурентних середовищах. У даному дослідженні розглядаються методи низькочастотної фільтрації, що аналізують архітектури, де вихідна величина демонструє лінійну або квадратичну залежність від амплітуди вхідного сигналу. Ці фільтрувальні механізми функціонують шляхом когерентного агрегування детермінованих елементів сигналу, дозволяючи випадковим шумовим компонентам накопичуватися некогерентно. Цей процес призводить до конструктивного посилення енергії сигналу поряд із сублінійним зростанням потужності шуму, що суттєво покращує співвідношення сигнал/шум (С/Ш). Прямокутний імпульс було використано як модель сучасних хвильових форм цифрового зв'язку для обох типів фільтрів. Проведено всебічний статистичний аналіз у часовій та частотній областях, оцінюючи такі метрики, як дисперсія, математичне сподівання, коефіцієнти кореляції та С/Ш. Для об'єктивної оцінки ефективності фільтрації запроваджено нову метрику під назвою «коефіцієнт корисної дії», яка вимірює приріст надійності виявлення. Моделювання додатково досліджувало реакції напруги огинаючої від ідеального смугового фільтра, збудженого прямокутними імпульсами різної тривалості, імітуючи системи з низькою ймовірністю перехоплення (LPI). Дослідження підтверджує, що приховані сигнали можуть бути ефективно виділені за допомогою двовимірного оцінювання щільності правдоподібності. Системна інтеграція вузькосмугової низькочастотної фільтрації підвищила завадостійкість виявлення повітряних цифрових сигналів на 23%, посилюючи операційну стійкість у ворожих середовищах, актуальних для електронної боротьби та радіорозвідки.

Ключові слова: Приховане виявлення сигналів, квадратична фільтрація, завадостійкість, цифрове радіовипромінювання, низькочастотна фільтрація, когерентне підсумовування, співвідношення сигнал/шум (С/Ш), безпечний зв'язок, оцінка щільності правдоподібності.

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