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Signal Processing under Presence of Low Frequency Noise in the Low Speed Data Channel

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ABSTRACT

This paper explores the impact of low-frequency additive noise and interference on communication channels. It focuses on a specific channel that is used for both receiving and transmitting signals in both unmanned vehicle groups and the Internet of Things systems. To ensure the efficient operation of the receiving and transmitting devices, a low-power, narrowband signal is employed, along with a slow data transmission rate. The work discusses the use of fractal analysis to mitigate the effects of low-frequency flicker noise and introduces the fractal Brownian motion model for characterizing low-frequency flicker noise statistically. It also calculates the parameters of the communication channel under the influence of low-frequency interference. A maximum likelihood algorithm for signal detection in the presence of additive fractal jamming has been created. The findings suggest that employing fractal models can enhance signal processing efficiency in the presence of background noise, even when there are no other significant differences between the signal and noise. Recommendations are made for integrating signal processing techniques that can handle the low-frequency, fractal nature of the spectral power density.

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1. Introduction

Under conditions of high frequency density of signals in the air, ensuring reliable transmission of information with minimal distortion is an actual task of radio engineering. When creating a communication channel of a large volume, the broadband signals with a large base value and a high carrier frequency are used. At the same time, a small amount of information is often required, for ex ample, sensor readings, telemetry measurements, and so on. In this case, a fairly effective solution is the use of broadband and low-power signals. New access technologies targeting IoT, such as enhanced Machine Type Communications (eMTC), Narrow-Band IOT (NB-IoT), and the 5th generation mobile networks (5G) are currently under development. Massive numbers of MTC services require low-cost devices with low power consumption profiles [1–3]. For this purpose, in the paper algorithms for optimal processing the signals based on probabilistic models are used [4]. The most general formulation of the problem and the model of signals and interference are implemented in the estimation-correlation compensation approach [5–7]. The statistical approach is also used in processing the signals with fractal properties [8]. Application of statistical methods is in terpretation of the correlation integral as the probability of non-exceeding the distance between vectors of a given value [9–12]. As the aim of investigation, improving the statistical approach is chosen. The design targets of NB-IoT include low-cost devices, high coverage (20-dB improvement over GPRS), long device battery life (more than 10 years), and massive capacity (greater than 52K devices per channel per cell). Latency is relaxed although a delay budget of 10 seconds is the target for exception reports. Since NB-IoT design is based on existing LTE functionalities, it is possible to reuse the same hardware and, also, to share spectrum without coexistence issues. This provides a low-cost and fast deployment of NB-IoT using existing infrastructure. For sites with newer equipment, the NB-IoT can be supported via software upgrade. However, older equipment may not be able to support both LTE and NB-IoT simultaneously and a hardware upgrade may be required. In this case, the NB-IoT deployment can be phased in where existing cell sites are incrementally upgraded to the NB-IoT. This will allow fast roll-out of NB-IoT without the need to upgrade the hardware on all sites. With such a phased roll-out, there will be a partial deployment of the NB-IoT until all sites are fully upgraded.

2. Fractal Brownian Motion as a Model of Additive Flicker Noise

Fractal Brownian motion (FBM) is used as a model of fractal interference [13]. Hurst exponent H is a main characteristic of the FBM. Dimension of FBM is determined by D = 2 - H for one-dimensional FBM. The fractal Brownian motion is a Gaussian random process. Its properties are completely determined by correlation matrices for one-dimensional signal

$$M\left\{\left(\mathbf{X}(t_2)-\mathbf{X}(t_1)\right)\left(\mathbf{X}(t_4)-\mathbf{X}(t_3)\right)\right\}$$
$$=0.5\sigma^2\left[-(t_2-t_1)^{2H}+(t_2-t_3)^{2H}+(t_1-t_4)^{2H}-(t_1-t_3)^{2H}\right],$$

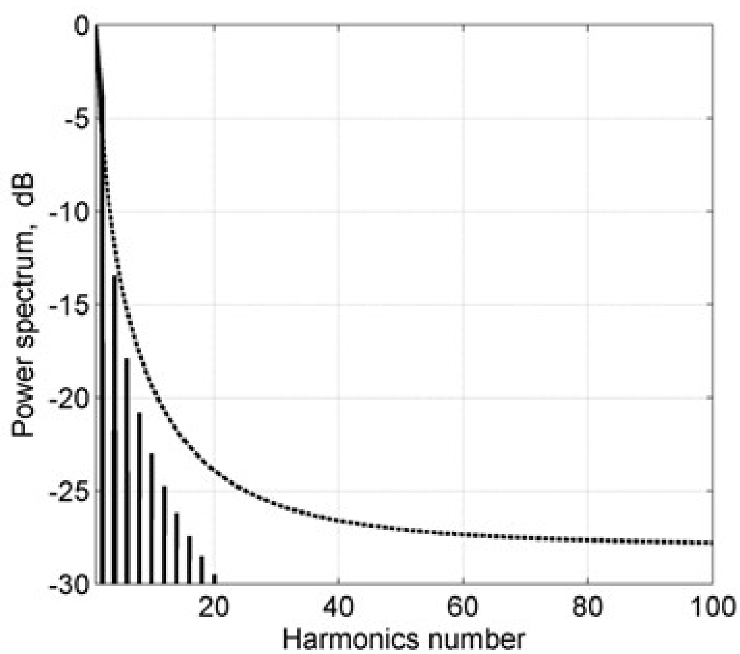

Figure 1. Power spectrum signal (solid line) and flicker noise (dashed line) on number of harmonics

where the matrix R, which contains correlations of all possible increments M = 0.5 $\times$ N(N-1) has the size of M $\times$ M and is formed by given N samples: $\Delta x_m = x(t_i) - x(t_j)$, i = 1,..., N, j = 1,...,i,m = 1,...,M, Consider non- correlated samples of FBM in spectral eld. In such cases, the correlation equals $M\{\Delta X_I \Delta X_j\} = \delta_{ij} D_X \Delta t^{2H}{}_i$, where δ_{ij} is the Kronecker delta, i = 1,...,N -1. In this case, the matrix R is diagonal and its determinant equals det R = $D^N{}_X \prod_{n-1}^{N-1} \Delta t_n{}^{2H}$.

Figure 1 represents the FFT power spectrum of signal (solid line) and flicker noise (dashed line) spectra for H = 0:5, amount of samples K = 800. It is proved, that increasing the signal duration leads to spectrum transfer to low frequency area with high intensity of icker noise spectrum. It leads to decreasing noise resistance.

3. Estimation of Signal Correlation Matrix

In many cases, vector of observed signal samples is represented as *x(t) = V s(t)+ n(t)*, where n(t) is a vector of flicker noise samples with zero mean and correlation function R_n, *s(t)* is a vector of signal samples, *V* is a transformation matrix. Suppose that random signal s is observed in the known vector *x*. The random signal and flicker noise vector n are described as a model of fractal Brownian motion with different Hurst exponent. This parameter is used as a detection statistics for signal detection at the background of noise.

Consequently, correlation matrices of signal and noise are as follows:

$$\boldsymbol{R} = \frac{q_F}{2}[|n_1|^{2H} + |n_2|^{2H} - |n_1 - n_2|^{2H}], n_1, n_2 = 1, \ldots, N,$$

where n_1,n_2 are the counting numbers of signal and noise samples.

As it follows from the optimal processing theory of determined signal at the background of Gaussian noise, the optimal impulse response equals $w_{opt} = \boldsymbol{S}^T \boldsymbol{R}_N^{-1}$. As FBM increments have Gaussian distribution law and noise samples are additive and independent, it is possible to calculate the signal estimate and correlation matrix of errors.

$$\hat{s} = (\mathbf{R}_x^{-1} + \mathbf{R}_n^{-1})^{-1}\mathbf{R}_n^{-1}Y = (\mathbf{R}_n\mathbf{R}_x^{-1} + I)^{-1}Y$$

$$R_{\hat{s}} = (\mathbf{R}_x^{-1} + \mathbf{R}_n^{-1})^{-1} = (\mathbf{I} + \mathbf{R}_x\mathbf{R}_n^{-1})\mathbf{R}_x$$

where R_x is the correlation matrix of the observation vector, I is the unity matrix, $*^{-1}$ is the operation of matrix inversion. Results of calculation are presented at Figures 2-4. In the case of fixed value of signal power and optimal processing, the output signal-noise ratio increases monotonically with increasing the signal duration. Along with this, it is proved that increasing the output signal-noise ratio is limited by the fixed value. This is determined by the fact that spectrum of longer signal is focused in the area of low frequencies, where the flicker noise spectral power density increases. Processing quality is estimated by the signal-noise ratio calculated in spectral field.

$$q = \sum_{m=1}^{M} \frac{2|\underline{S}_m|^2}{\frac{G_1}{m^{2H+1}} + G_0}$$

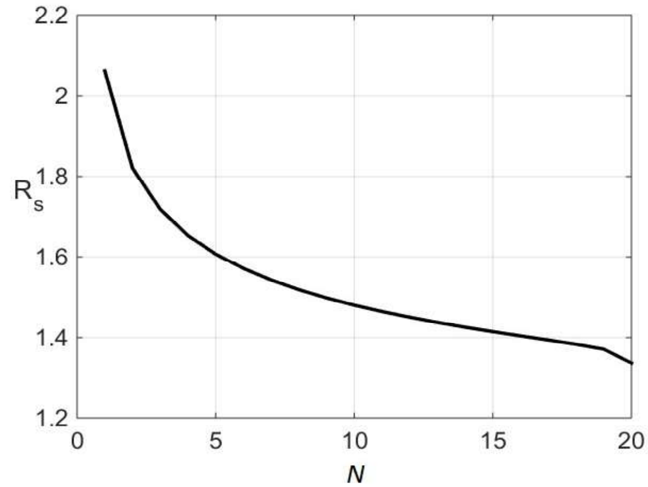

Figure 2. Dependency of error variance on sample number, $H = 0.3$, $H_2 = 0.5$

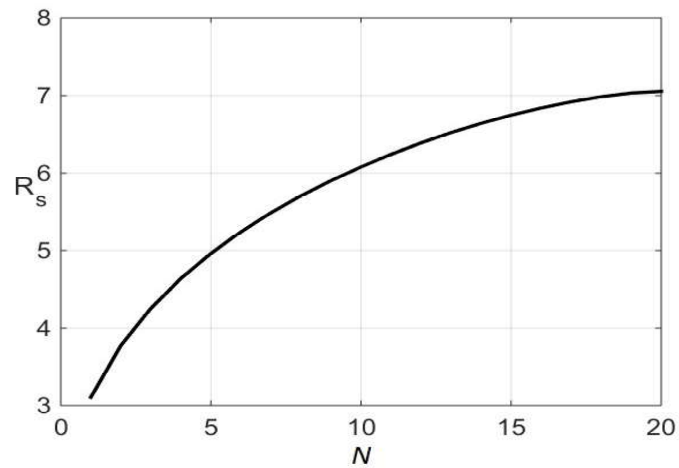

Figure 3. Dependency of error variance on sample number, $H_2 = 0.8$; H_2 .5

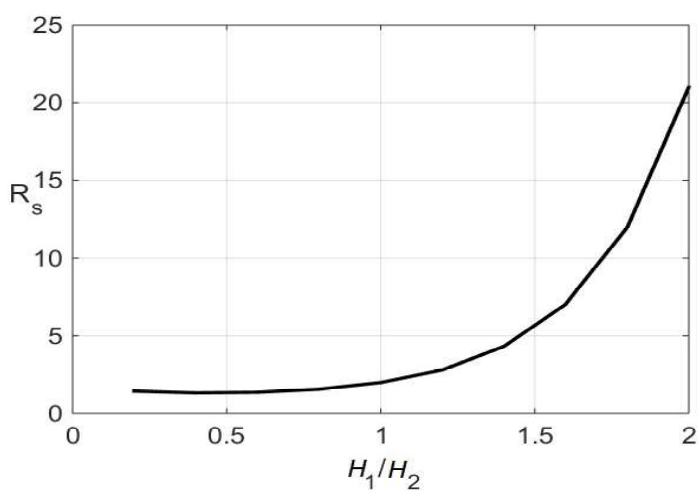

Figure 4. Dependency of error variance on Hurst exponents ratio, $H_2 = 0.5$

4. Conclusion

As a result of evaluation, it is shown that methods of the theory of optimal statis- tical solutions can be successfully applied, also, to processing the fractal signals against the background of additive fractal noise. The basis for the effectiveness of statistical methods is the irregular character, as well as the relatively large amount of the observable data. Under these conditions, the statistical description of fractal signal is produced by various methods: the use of a one-dimensional and two-dimensional fractal Brownian motion model, and a statistical description of distances between vectors in a pseudo-phase space. This approach allows us to obtain processing algorithms based on the theory of optimal statistical solutions for solving various problems: detection, discrimination, delineation of boundaries, estimation of parameters, and analysis of the processing efficiency. At the same time, the statistical description is not obtained for all fractal signals and their characteristics. This makes important to continue research in this direction. Optimal signal processing at the background of flicker noise provides the predetermine .quantity of information in the case of ultra-low-power signal of IoT. To increase the quantity of the information IoT, the optimal waveform is needed. The matched filter is not optimal at the background of the flicker noise. When the matched filter is used, the optimal signal width may be evaluated. Note that a continuous waveform observes at the background of a fading, which is caused multipath waveform propagation. Therefore, the MIMO technology have to be used for IoT applications. The power efficiency depends on many conditions not only on receiver sensitivity. Therefore, simplification of signal processing algorithm has to be performed when the optimal processing is developed.

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