Visnyk NTUU KPI Seriia – Radiotekhnika Radioaparatobuduvannia, 2022, Iss. 88, pp. 42–49

UDC 621.39

Iterative Method for Noise Power Estimating at Unknown Spectrum Occupancy

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Noise power estimating is the core of modern radio monitoring systems for solving tasks of spectrum occupancy calculation, detecting and estimating signal parameters. The growth of electronic devices number leads to an increase in overall noise level and its fast fluctuations. These devices often emit pulses or separate carriers. Since radio monitoring equipment must operate under these conditions, it may not be possible to exclude these components from radio noise measurements. It was shown that in some cases an increase in the noise power by 20% of the expected value leads to an increase in the false alarm rate by an order. The aim of this work is to develop and explore an iterative method for estimating the noise power with an unknown occupancy of the analysis frequency band, which will have low computational complexity and estimates independent of spectrum occupancy. The essence of the proposed method consists in two-threshold division of frequency samples into signal and noise by a statistical criterion using the coefficient of variation of spectral estimates. Thresholds are selected for a given false alarm rate. When threshold value of the coefficient of variation is exceeded, it is considered that there are occupied frequency channels in the spectrum, and each frequency sample is compared with the second threshold. Those samples that have exceeded the threshold are considered signal, and the rest – noise. The described procedure is then repeated for noise samples until all signal samples have been discarded. Also was developed method for calculating the noise power in time domain using the obtained noise power in frequency domain. Algorithm evaluation has shown that it remains robust for spectrum occupancy up to 60%. In this case, the relative error in estimating the noise power does not exceed 5%, and the average number of iterations of the algorithm grows with increasing occupancy and does not exceed 10.

Keywords: spectrum occupancy; iterative method; coefficient of variation; periodogram; radio monitoring; noise power

DOI: 10.20535/RADAP.2022.88.42-49

Introduction

In modern radio monitoring systems noise power estimating problem is essentially important for solving tasks of spectrum occupancy calculation, detecting and estimating signal parameters. Knowing noise level can improve processes of signal recognition and demodulation. Uncertainty of the noise power is mainly due to variations in the gain of the low-noise amplifier, calibration errors and the presence of interference. If the first two factors lead to slow changes in the noise level and can be easily taken into account, the latter leads to its fast changes [1]. Interference is mainly due to an increase of electronic systems number, in particular those that use low-bandwidth signals with low power density, and leads to an increase in the overall noise level and its oscillations. Therefore, considerable attention is paid to measurement of such kind of noise [2]. If there is no predominance of single radio sources at the measurement site, noise characteristic has a normal amplitude distribution and can be considered as white Gaussian noise. However, in the conditions of high density of electronic devices, which are often found in large cities and residential areas, it is virtually impossible to find a place where at least temporarily not dominated by noise or radiation generated by a single source. These sources often emit pulses or separate carriers. As radio monitoring equipment must operate in such conditions, it may not be possible to exclude these components from radio noise measurements. In addition, in some cases, the signals may be weaker than the background noise. As a result, it is difficult to detect and locate a weak signal with low power density, using existing radio control systems with low sensitivity. To extract signals from background noise the newest processing methods should be used in future spectrum control systems [3].

The resulting estimate of frequency band occupancy depends on the value of the threshold, which is determined by the noise power [4]. To detect as much radio emissions as possible, regardless of their power, it is advisable to use a dynamic threshold, which is calculated regarding on the current noise power. Therefore, the development of methods for estimating noise power in conditions of dynamic changes in the electronic environment will provide a reliable estimates of spectrum occupancy, as well as detection of low power density signals by measuring changes in background noise level.

1 Related works

The methods of estimating noise power proposed in the literature are mainly based on statistical analysis of signal spectra, autocorrelation function and calculation of eigenvalues of the covariance matrix.

In [5, 6], a consecutive mean excision (CME) algorithm for detecting signal samples is proposed, which can be used to estimate the noise power. Algorithms such as CME are slow, as they take over a large number of frequency samples, and some modifications need sort operation. A similar approach is also proposed in [7]. In [8], the noise power is estimated from the free adjacent frequency channel. The problems of estimating the noise level for cases of its slow change in time, frequency dependence and in the presence of signals in the analyzed frequency band are considered in [9]. Initially, the Forward CME (FCME) algorithm was used to estimate the noise power. After that, another algorithm constantly monitors significant changes in the noise level in the frequency domain, and in case of its occurrence, the FCME algorithm is used again. It is shown that the proposed approach has less computational complexity compared to CME. However, the algorithm for detecting changes in the noise level requires a complex procedure for calculating hyperparameters, which values depend on the signal-to-noise ratio (SNR). In [10] an iterative method of simultaneous estimation of channel state and noise power using EM-algorithm is proposed, and in [11] noise level is measured using maximum likelihood estimates at free time intervals. If there are OFDM signals with cyclic prefix in the analyzed frequency band, it is proposed to estimate the noise power in [12] by analyzing the autocorrelation function. In [13], the noise variance is estimated based on the assumption that signal can be described by a system of Yule-Walker equations with known coefficients. In [14] noise power is estimated by spectrogram processing. It is assumed that the probability of a signal occurrence in a given frequency-time domain is 0.5. When deviating from this value, as well as at high SNR values, the probability of false alarm rate deviates from the required. In [15], noise and signal levels are proposed to be estimated in the frequency domain using the method of maximum likelihood by iterative approximation. The most reliable way to prove whether a frequency band contains only white Gaussian noise is to use the mathematical concept of singular value decomposition. This is the most practical way to choose frequency band for measuring the noise level [1]. In [4] to detect the maximum number of signals, it is recommended to define the threshold as a noise level plus 3-5 dB. The noise level is measured at an unused frequency or calculated as an average of 20% of the frequency samples with a minimum values. However, this approach will result in reduced sensitivity to signal detection at low SNR values, which is an actual today problem [16].

A common drawback of these works is absence of accurate estimates of the measured noise power for different levels of spectrum occupancy, which will significantly affect the performance of signal processing algorithms.

2 Problem statement

The aim of the work is to develop and explore an iterative method of estimating the noise power at unknown occupancy of analyzed frequency band, which will have low computational complexity and independent of spectrum occupancy estimates.

3 Dependence of false alarm probability on noise power

Before describing the method of estimating the noise power, we will establish how the probability of false alarm depends on the deviation of the actual value of the noise level from the expected one. This will further make it possible to formulate the requirements for the required accuracy of noise power estimation with the allowable value of the false alarm rate error.

To separate received samples into signal and noise one the Neyman-Pearson criterion is most often used [17]. In this approach, the false alarm rate P_F is fixed at some level, and decisive function is found by maximizing the probability of detection. In any case, the test is to compare the value of a function with threshold. Threshold value is chosen based on the value of false alarm rate. Most signal processing is performed in time or frequency domains. Therefore we will consider these cases.

Noise power determines the false alarm rate at a fixed threshold value. At Fig. 1 is shown dependence of the ratio of the actual probability of false alarm rate P_F to its need value P_{F_0} with increasing standard deviation (SD) of zero-mean Gaussian noise σ_ξ. Threshold for P_{F_0} was calculated for σ_{ξ_0}. From this figure it is seen that when the required value of the probability of false alarm rate P_{F_0} decreases, its deviation from the actual value of P_F increases for a fixed noise SD σ_ξ. Thus, when the deviation of the expected value of noise SD from the actual is only 20% the value of P_F increases by about 1.4 times for $P_{F_0} = 0.1$ and almost an order for $P_{F_0} = 0.0001$. Moreover, the P_F deviation rate will be the maximum for small values of $\sigma_\xi / \sigma_{\xi_0}$. For $\sigma_\xi \to \infty$ the error in the value of the false alarm rate will be $P_F / P_{F_0} \to 0.5$.

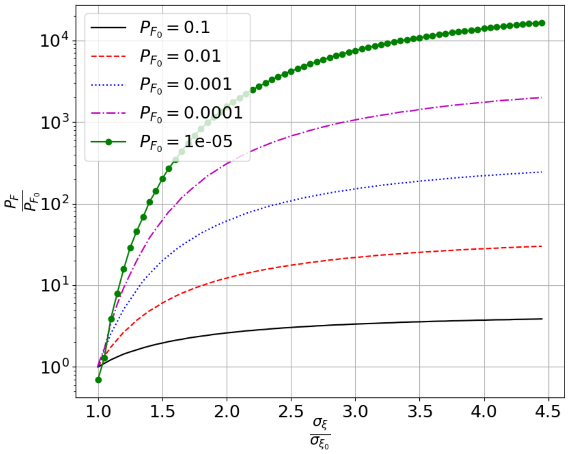


Fig. 1. Dependence of the false alarm rate increasing via noise SD

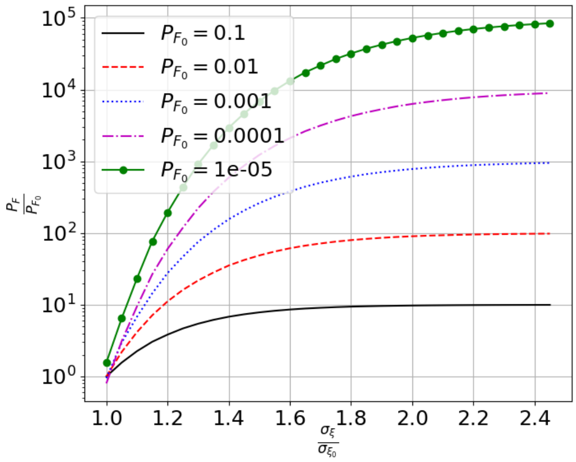


Fig. 2. Dependence of false alarm rate increasing via noise SD for $N_{FFT} = 1024$, $N = 4N_{FFT}$ and $R = 0.5N_{FFT}$

Similar curves can be constructed for the case of signal processing in the frequency domain using the Welch periodogram. The length of the analysis sequence is N samples, the length of the fast Fourier transform (FFT) is N_{FFT} and the overlap between the windows is R samples. At Fig. 2 is shown the dependence of false alarm rate increasing via noise SD increasing for $N_{FFT} = 1024$, $N = 4N_{FFT}$, $R = 0.5N_{FFT}$ and Hamming window function. If the value of noise SD deviates from the expected at 20%, the obtained value of the probability of false alarm rate will be greater than expected by almost 4 times for $P_{F_0} = 0.1$ and 65 times for $P_{F_0} = 0.0001$. With increasing FFT length depicted at Fig. 2 dependences practically do not change. As the overlap between the windows R decreases, the curves will be flatter, and as N increases, the curves will be steeper. This is due to the dependence of noise SD in the frequency domain on the parameters of the periodogram: with decreasing R noise SD will increase, and with increasing N – decrease. For the frequency domain for $\sigma_\xi \to \infty$ the error of false alarm rate will be $P_F/P_{F_0} \to 1$.

4 Iterative method for noise power estimating in frequency domain

Iterative algorithms are often used in signal processing due to their adaptability and recursive representation capabilities [17]. They provide an approximate result and have less computational complexity compared to analytical methods.

In time domain, noise and signal can be contained in all samples to be analyzed. In this case, it is difficult to estimate the noise power. In the frequency domain, signal samples are superimposed on noise only in occupied frequency channels. Therefore, it is advisable to estimate noise power in frequency domain.

In [18, 19] was proposed an iterative method of detecting occupied spectrum bands. Its essence is the two-threshold separation of frequency samples into signal and noise according to the statistical criterion using the coefficient of variation of spectral estimates. First, the coefficient of variation is calculated for power spectral density (PSD) samples and compared with the threshold value. The threshold is selected for a given probability of erroneous assignment of noise samples to signal.

If the threshold value of the coefficient of variation is exceeded, it is assumed that there are occupied frequency channels in the spectrum and each frequency sample is compared with the second threshold. This threshold is chosen similarly to the previous one. Those samples that exceed the threshold are considered signal, and the rest – noise. The described procedure is then repeated for noise samples until all signal samples will be detected.

Using the above ideas in Fig. 3 shows the algorithm for estimating the noise power in frequency domain. We will use the Welch periodogram to calculate the PSD of the received signal.

In block 1 we enter such parameters: $\mathbf{x}$ – vector of received signal samples; M – number of averaged spectra; $\mathbf{w}$ – vector of window function samples; $\mathbf{Q_{tr}}$ – vector of threshold values for coefficient of variation for a given probability of false alarm rate; P_F – required false alarm rate in frequency domain; n_s – number of detected signal samples.

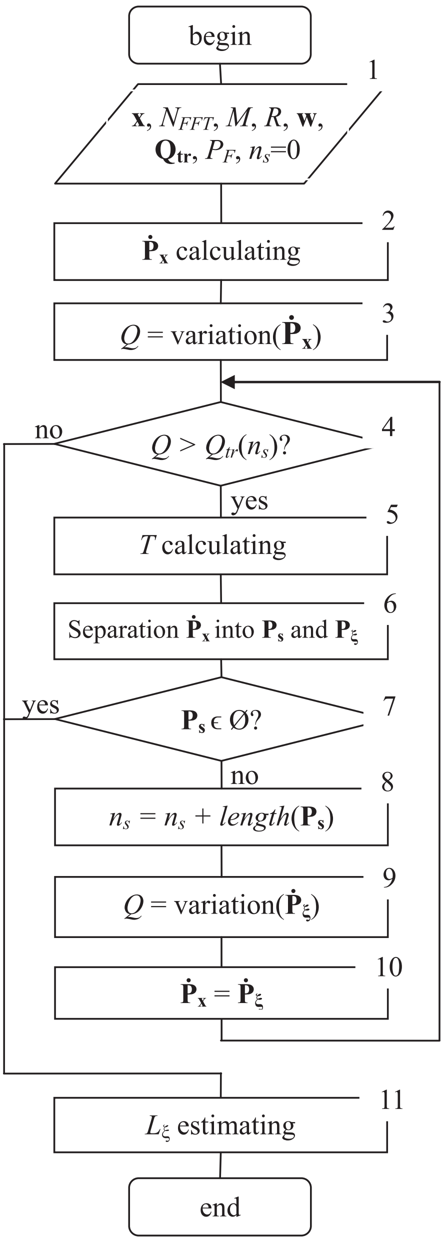


Fig. 3. Block diagram of noise power estimation algorithm

In block 2, the PSD of the signal is calculated using the Welch peroiodogram. First, the spectrum of the window-weighted j-th signal segment is calculated by the following expression:

$$X_j(k) = \sum_{n=0}^{N_{FFT}-1} x(n)\, w(n)\, e^{-j2\pi \frac{kn}{N_{FFT}}}. \tag{1}$$

The accumulation of M energy spectra will give estimate of PSD:

$$P_x(k) = \sum_{j=1}^{M} |X_j(k)|^2, \tag{2}$$

which is then normalized to energy

$$\dot{\mathbf{P}}_{\mathbf{x}} = \frac{\mathrm{P_x(k)}}{\sum_{k=0}^{N_{FFT}-1} \mathrm{P_x(k)}}. \tag{3}$$

In block 3, the value of the PSD coefficient of variation Q is calculated, which in block 4 is compared with the threshold value for a given number of detected signal samples $Q_{tr}(n_s)$. The probability density function of noise samples has central chi-square distribution with M degrees of freedom. Then, for the separation of signal and noise samples in the frequency domain, the threshold value is calculated in block 5 by the following expression [18]:

$$T = \frac{1}{N_{FFT} - n_s}\left(1 - \frac{1}{8.64M} + u\sqrt{\frac{1}{8.64M}}\right)^3, \tag{4}$$

where

$$u = \frac{1.24 + 0.85H^{0.657}}{1 + 0.0001H^{-3} + \frac{2.38}{H}}, \quad H = -\ln\left(\frac{P_F}{1 - P_F}\right). \tag{5}$$

Using this threshold in block 6 vector $\dot{\mathbf{P}}_{\mathbf{x}}$ is divided into the vectors of signal $\mathbf{P_s}$ and noise $\mathbf{P}_\xi$ samples. If at the current iteration of algorithm signal samples is not detected (block 7), the noise level L_ξ (block 11) is estimated by the following expression:

$$L_\xi = \frac{1}{N_\xi} \sum_{k=1}^{N_\xi} P_\xi(k), \tag{6}$$

where $N_\xi = N_{FFT} - n_s$ – number of noise samples.

In block 8 for every iteration the number of signal samples n_s is updated. In block 9, the value of the coefficient of variation Q is calculated for the energy-normalized vector for noise samples $\dot{\mathbf{P}}_\xi$. In block 10, the previous vector of frequency samples $\dot{\mathbf{P}}_{\mathbf{x}}$ is replaced by the vector of noise samples $\dot{\mathbf{P}}_\xi$. After that, among the noise samples we again search for signals. Evaluation of the algorithm continues until all signal samples will be detected and rejected.

For samples of raw data, it is recommended to perform one measurement with duration at least 0.5 s every 10-30 s [1]. The proposed algorithm will give an adequate estimate of noise if its level is approximately the same at all analyzed frequencies.

5 Noise power calculation in time domain

To determine the start and end time of a signal in a frequency channel, it is necessary to know the noise SD to set the desired threshold value. Noise SD in time domain will be calculated using Parseval's theorem [17] according to such expression:

$$\sum_{n=0}^{N-1} |x_\xi(n)|^2 = gL_\xi, \tag{7}$$

where $N=(M-1)R+N_{FFT}$ – number of samples for periodogram calculation; g – normalization coefficient, which depends on the parameters of the periodogram and the type of window function.

If noise is zero-mean, then its variance can be calculated by this expression:

$$\sigma_\xi^2=\frac{1}{N}\sum_{n=0}^{N-1}\left|x_\xi(n)\right|^2. \quad (8)$$

The value of g coefficient is determined based on the fact that N samples of the signal in the time domain must contain the same amount of energy as M windowed segments of N_{FFT} length. Then the value of g can be determined from the following expression:

$$g=\frac{N}{M\sum\limits_{n=0}^{N_{FFT}-1}\left|w(n)\right|^2}. \quad (9)$$

Taking into account expressions (7-9) we can calculate noise SD with such equation:

$$\sigma_\xi=\sqrt{\frac{L_\xi}{M\sum\limits_{n=0}^{N_{FFT}-1}\left|w(n)\right|^2}}. \quad (10)$$

Having σ_ξ estimate and assuming that the noise has normal distribution, we can calculate the value of the threshold and for the required false alarm rate in the time domain using expression 5.

Also we can calculate SNR in i-th frequency channel:

$$SNR_i=\frac{\sigma_{is}^2-\sigma_{i\xi}^2}{\sigma_{i\xi}^2}, \quad (11)$$

where σ_{is}^2 – noise variance in i-th frequency channel with width Δf_i; $\sigma_{i\xi}^2$ – noise variance in given frequency channel.

If the noise SD σ_ξ was calculated for bandwidth $\Delta\Pi$, than for channel with bandwidth Δf_i noise power can be calculated according such expression:

$$\sigma_{i\xi}^2=\sigma_\xi^2\left(\frac{\Delta f_i}{\Delta\Pi}\right)^2. \quad (12)$$

Similar calculations can be performed in the frequency domain:

$$SNR_i=\frac{\sum\limits_{k_{i\,\min}}^{k_{i\,\max}}P_x(k)}{\left(k_{i\,\max}-k_{i\,\min}\right)L_\xi}-1, \quad (13)$$

where $k_{i\,\max}$ and $k_{i\,\min}$ – maximum and minimum value of frequency sample index in i-th channel.

Calculated values of SNR can be used to predict the quality of signals detection or demodulation when designing electronic systems for operation in sophisticated electromagnetic environments.

6 Simulations and numerical results

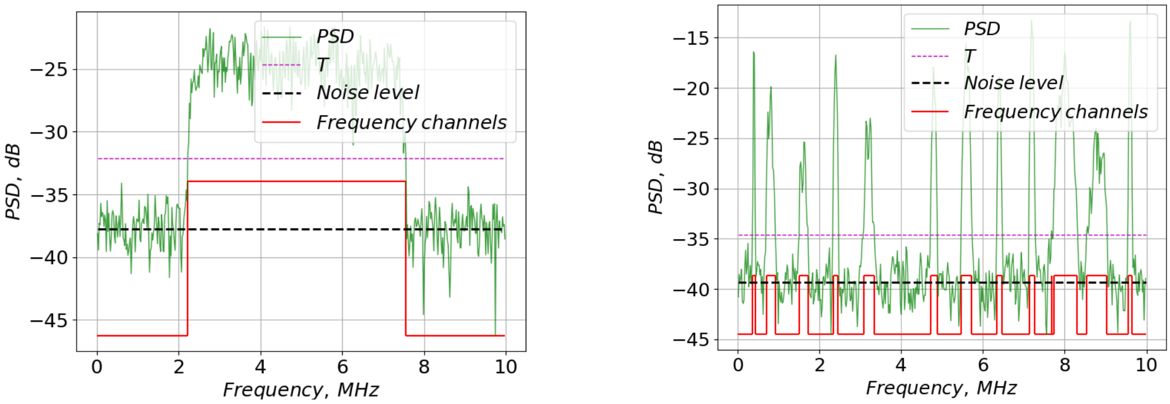
In this paper bandwidth occupancy η will be calculated as the ratio of the sum of bandwidths of all occupied frequency channels to the analyzed bandwidth $\Delta\Pi$. We will study the algorithm for two typical spectrum shape cases. One for signals with almost rectangular spectrum envelope (OFDM, filtered PSK) and another for the rest spectrum shape envelopes. The occupancies of frequency band was chosen such that developed algorithm will remain stable.

For the first case analyzed frequency band contains one OFDM signal, which occupies from 3% to 60% of the bandwidth $\Delta\Pi$. For the second case, in frequency band $\Delta\Pi$ we will place from 1 to 12 narrowband signals with different powers and bandwidths. Spectrum occupancy will vary from 1% to 30%. Fig. 4a shows result of OFDM signal processing with a spectrum width of $0.58\Delta\Pi$ with 10 dB SNR and the following parameters of the periodogram: $M=7$, $N_{FFT}=1024$, $R=512$, $w=$ hamming. False alarm rate P_F was chosen at 0.01. In Fig. 4b is shown the case of narrowband signals processing. The noise level is calculated according to expression 6 at signal-free frequencies.

Fig. 5a demonstrates dependence of the relative error of noise power estimate δ via occupancy. For one OFDM signal δ does not exceed 1%. Numerical results have shown that for the OFDM signal, the algorithm with the above parameters remains stable for occupancies up to 60%. At higher occupancies, the algorithm gives inflated estimates of the noise power. For direct sequence spread spectrum signals proposed algorithm remains stable for signal bandwidth up to $0.4\Delta\Pi$. At higher occupancies, it is necessary to better smooth PSD by accumulating more spectrum realizations M.

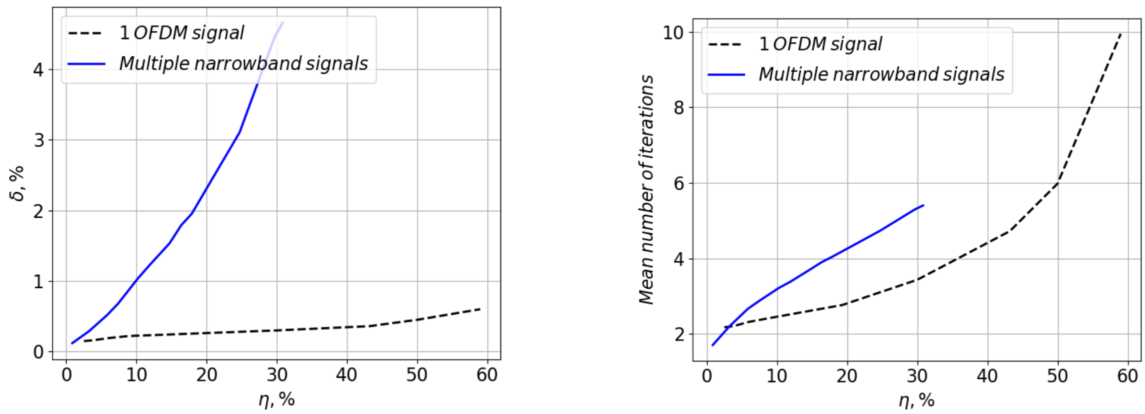
The dependence of the average number of iterations of the algorithm required to estimate the noise power is shown at Fig. 5b. When the band occupancy is about 20% of narrowband signals with different spectrum widths and powers, the average number of iterations is about 4, and the error is about 3%. For comparison, in case of presence in analyzed frequency band one OFDM signal with a spectrum width of $0.2\Delta\Pi$ under constant preconditions, the average number of iterations did not exceed 3, and the estimation error was less than 0.5%.

The influence of the window function on the value of the error in estimating the noise power and the average number of iterations of the algorithm is insignificant and for practical applications it is advisable to choose the window for the required level of sidelobes. Only the rectangular window compared to other windows for the OFDM signal has a relative error of estimating noise power by an average of 2% while for other windows it does not exceed in average 0.5%.



(a) (b)

Fig. 4. Spectrum after processing for first (a) and second (b) cases of signal environment



(a) (b)

Fig. 5. Relative error of noise power estimate (a) and mean number of iterations (b) via occupancy

If the signals dynamic range exceeds 30-40 dB or in case of very high SNR, which leads to out-of-band radiation, the use of window functions with low sidelobes will provide less error for noise power estimates. It is recommended to use nuttall and blackman-harris windows to obtain stable estimates of noise power.

As the number of analyzed signal segments M increases, the values of the relative error and the average number of iterations to obtain an estimate of the noise power decrease. Increasing the overlap between adjacent windows R from 0.5 to 0.75 has little effect on the error value. Increasing FFT length reduces the error value with a slight increase in the number of algorithm iterations.

Conclusions

The scientific novelty of the obtained result is the development of an iterative method for estimating the noise power at unknown occupancy of analyzed frequency band, which has low computational complexity. The result is achieved by two-threshold iterative separation of frequency samples into signal and noise according to the statistical criterion using the coefficient of variation of spectral estimates. The algorithm remains stable for bandwidth occupancy up to 60%. The relative error in noise power estimating does not exceed 5%, and the average number of iterations of the algorithm is not more than 10. The developed algorithm should be used to improve the performance of radio monitoring systems.

Prospects for further research in this area should focus on improving the proposed method to process spectrum bands with higher than 60% occupancy levels.

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Ітеративний метод оцінювання рівня шуму при невідомій зайнятості смуги частот аналізу

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Оцінювання потужності шуму є ключовим елементом сучасних систем радіомоніторингу для вирішення завдань визначення зайнятості смуги частот, виявлення і оцінювання параметрів сигналів. Зростання кількості радіоелектронних пристроїв призводить до зростання загального рівня шуму і його різких коливань. Ці пристрої часто випромінюють імпульси або окремі несучі. Оскільки обладнання радіомоніторингу має працювати в таких умовах, виключити ці складові з вимірювань радіошуму може виявитися неможливим. У роботі показано, що в деяких випадках збільшення рівня шуму від очікуваного на 20% призводить до зростання ймовірності хибної тривоги на порядок. Метою роботи є розроблення та дослідження ітеративного методу оцінювання рівня шуму при невідомій зайнятості смуги частот аналізу, що матиме невисоку обчислювальну складність та незалежні від завантаженості оцінки. Сутність запропонованого методу полягає в двопороговому розділенні частотних відліків на сигнальні та шумові за статистичним критерієм із використанням коефіцієнта варіації спектральних оцінок. Пороги обираються для заданої ймовірності хибної тривоги. У разі перевищення порогового значення коефіцієнта варіації вважається, що у спектрі є зайняті частотні канали і кожен частотний відлік порівнюється з другим порогом. Ті відліки, що перевищили поріг вважаються сигнальними, а решта – шумовими. Після цього описана процедура повторюється для шумових відліків до тих пір, доки не буде відкинуто усі сигнальні відліки. Розроблено методику розрахунку середньоквадратичного відхилення шуму в часовій області із використанням отриманого рівня шуму в частотній області. Дослідження алгоритму показали, що він залишається стійким для завантаженості смуги частот аналізу до 60%. При цьому відносна помилка оцінювання рівня шуму не перевищує 5%, а середня кількість ітерацій алгоритму зростає зі збільшенням завантаженості і складає не більше 10.

Ключові слова: зайнятість смуги частот; ітеративний метод; коефіцієнт варіації; періодограма; радіомоніторинг; радіочастотний спектр; рівень шуму

Итеративный метод оценивания уровня шума при неизвестной занятости полосы частот анализа

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Оценка мощности шума является ключевым элементом современных систем радиомониторинга для решения задач определения занятости полосы частот, обнаружения и оценки параметров сигналов. Рост количества радиоэлектронных устройств ведет к росту общего уровня шума и его резким колебаниям. Эти устройства часто излучают импульсы или отдельные несущие. Поскольку оборудование радиомониторинга должно работать в таких условиях, исключить эти составляющие из измерений радиошума может оказаться невозможным. В работе показано, что в некоторых случаях увеличение уровня шума на 20% от ожидаемого ведет к возрастанию вероятности ложной тревоги на порядок. Целью работы является разработка и исследование итеративного метода оценки уровня шума при неизвестной занятости полосы частот анализа, что будет иметь невысокую вычислительную сложность и независимые от загруженности оценки. Сущность предлагаемого метода состоит в двухпороговом разделении частотных отсчетов на сигнальные и шумовые по статистическому критерию с использованием коэффициента вариации спектральных оценок. Пороги выбираются для заданной вероятности ошибочной тревоги. При превышении порогового значения коэффициента вариации считается, что в спектре имеются занятые частотные каналы, и каждый частотный отсчет сравнивается со вторым порогом. Те отсчеты, что превысили порог, считаются сигнальными, а остальные – шумовыми. После этого описанная процедура повторяется для шумовых отсчетов до тех пор, пока не будут отброшены все сигнальные отсчеты. Разработана методика расчета среднеквадратического отклонения шума во временной области с использованием полученного уровня шума в частотной области. Исследования алгоритма показали, что он остается устойчивым для загруженности полосы частот анализа до 60%. При этом относительная ошибка оценки уровня шума не превышает 5%, а среднее количество итераций алгоритма растет с увеличением загруженности и составляет не более 10.

Ключевые слова: занятость полосы частот; итеративный метод; коэффициент вариации; периодограмма; радиомониторинг; радиочастотный спектр; уровень шума