

FAST SPECTROGRAM-BASED METHOD FOR IDENTIFYING RELATIVE SNR VARIATIONS IN NARROWBAND SIGNALS

Mihai NEGHINĂ

*“Lucian Blaga” University of Sibiu, Romania
“Nicolae Bălcescu” Land Forces Academy, Sibiu, Romania
mihai.neghina@ulbsibiu.ro*

Annamaria SÂRBU

*“Nicolae Bălcescu” Land Forces Academy, Sibiu, Romania
sarbu.annamaria@armyacademy.ro*

ABSTRACT

This paper proposes a fast, agile, low-complexity method for tracking relative signal-to-noise ratio (SNR) variations directly from spectrogram representations of narrowband signals. The approach operates on complex spectrogram values and employs simple statistical estimators, namely the maximum and median across frequency bins, to estimate a peak to background contrast metric within each time window. The proposed technique does not require access to the original time-domain signal, making it suitable for applications where only time-frequency representations are available. The method is evaluated using synthetic sinusoidal and chirp signals corrupted by additive white Gaussian noise over a wide SNR range (0–100 dB). Experimental results show a strong linear relationship between the estimated SNR-related metric, expressed in dB, and the reference SNR (namely in the 10–60 dB range), with correlation coefficients close to unity and low variability across different signal parameters. The proposed metric should be interpreted as a relative spectrogram SNR indicator rather than a calibrated SNR estimate, making it particularly suitable for low complexity applications such as interference/spectrum monitoring and signal quality tracking in systems where only spectrogram data is available or where computational simplicity is important.

KEYWORDS: narrowband signals, signal-to-noise ratio (SNR), spectrogram / time-frequency analysis

**Submission Received: 09 April 2026; Revised: 26 May 2026;
Accepted: 29 May 2026; Published: June 2026**

1. Introduction

The signal-to-noise ratio (SNR) is a key parameter in signal processing, widely used to quantify signal quality in applications such as wireless communications, spectrum monitoring, audio processing (Yao et al, 2016; Yook et al., 2013) or biomedical signal

analysis. Estimation of SNR is essential for tasks including signal detection, adaptive filtering or channel estimation, as well as for diagnostics in biomedical applications such as electroencephalography analysis (Milanović et al., 2019). In many of these domains, the ability not only to estimate SNR but also to

track its variations over time is useful for identifying anomalies, degradation, or interference.

Traditionally, SNR is acquired or computed directly from the signal using statistical estimation techniques, such as maximum likelihood (ML) estimators (Bellili et al., 2014), moment-based methods (Treviño, Benammar & Roque, 2024), or autocorrelation-based approaches (Kim, Ryu & Kim, 2011). ML estimators generally provide high accuracy but require significant computational resources and long observation intervals (Moazzeni et al, 2012). In contrast, autocorrelation-based methods offer reduced complexity by exploiting the statistical independence of noise and the correlation properties of the signal, making them suitable for practical implementations in AWGN channels (Chen & Huang, 2007). Simpler statistical estimators offer reduced computational complexity but may exhibit degraded performance in challenging conditions, particularly at low SNR levels where accurate estimation is most critical (Harris & Dick, 2012). More recent approaches include deep learning-based estimators, based on large datasets and complex models intended to improve estimation performance in challenging environments, at the cost of increased computational complexity (Jeevangi et al., 2022; Valadão et al., 2024). Recent studies in cognitive radio systems have shown that spectrogram-based representations, especially when combined with advanced processing techniques, can significantly improve spectrum sensing performance and robustness to noise, highlighting their relevance for dynamic and complex signal environments (Hassan et al, 2025).

In many practical scenarios, access to the raw IQ (In-phase and Quadrature) signal is limited or unavailable, and only time-frequency representations such as spectrograms can be used. This is common in applications involving stored data, visualization-based analysis, or distributed

sensing systems. Spectrogram-based methods have therefore been proposed, including approaches based on amplitude modulation spectrograms or image processing techniques, demonstrating their effectiveness in domains such as speech analysis and biomedical signal processing (Tchorz & Kollmeier, 2002; Vieira et al, 2014).

The method proposed in this paper completes the available public literature by introducing an agile approach for detecting SNR variations directly from spectrogram representations of narrowband signals, such as sinusoids and chirps. The approach is based on simple statistical estimators applied within each spectrogram time window, enabling a simple estimation of the contrast between the dominant spectral component and the background spectral level without requiring access to the original time-domain signal. By exploiting the structured energy distribution of narrowband signals in the time–frequency domain, the method provides a computationally simple way to track relative SNR variations in spectrogram data, making it potentially useful for applications such as interference monitoring and spectrum observation.

From a broader perspective, the proposed solution may support practical spectrogram-based monitoring tasks where rapid detection of relative SNR changes is important. The current evaluation is limited to synthetic signals affected by AWGN, while more complex electromagnetic environments involving non-Gaussian noise, multiple emitters or digitally modulated signals require further validation.

The remainder of the paper is organized as follows: section 2 describes the proposed method algorithm with subsections focused on generation of spectrograms and estimation of SNR variations. Section 3 presents the results and discussion on the experiments performed and section 4 concludes the paper with a discussion of findings and future research directions.

2. Proposed Method

The method is designed to operate without access to the original time-domain signal, relying instead on statistical properties extracted from the time–frequency representation, namely spectrograms. For completeness, section 2.1 describes the generation of spectrograms under controlled conditions, while section 2.2 presents the proposed method for estimating SNR variations. Both phases, generation of spectrograms as well as the implementation of the proposed algorithm are carried out in MATLAB.

2.1. Generation of the Spectrograms

The diagram for generating the spectrograms is illustrated in Figure no. 1.



Figure no. 1: *Diagram for spectrogram generation*
(Source: Authors' own conception)

For each generated noisy signal, only the complex spectrogram values are computed and processed directly. The corresponding image representations are not used in this stage of the analysis. This choice is motivated by the fact that the proposed method operates directly on the numerical spectrogram values (S) obtained using Short-Time Fourier Transform (STFT)-based processing, which preserve the full amplitude information required for estimation of signal and noise power. The

spectrogram is generated on rectangular windows of 1 second of signal, with 50% overlap, resulting in a spectral distance of 1 Hz between bins and a time spacing of 0.5 s between adjacent spectrogram columns.

An example of a 1 kHz spectrogram image at a SNR value of 15 dB is presented in Figure no. 2(a) while the corresponding histogram of the noise samples used to corrupt the signal at the SNR level of 15dB is presented in Figure no. 2(b).

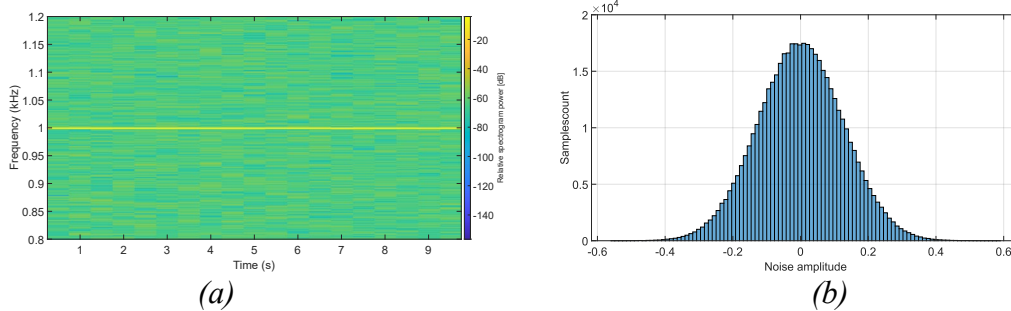


Figure no. 2: (a) *Spectrogram image corresponding to 1 kHz sine signal (SNR = 15 dB)*
(b) *Noise samples histogram for SNR=15 dB*
(Source: Authors' own conception)

2.2. Estimation of SNR Variations

The diagram for estimating SNR and SNR variation is shown in Figure no. 3. The spectrogram data acquisition refers to the reading of complex spectrogram values S , followed by the computation of normalized logarithmic spectrogram-power values, expressed in dB with eq. (1).

$$S_{dB} = 20 \log_{10}(|S|/F_s) \quad (1)$$

where S represents the complex spectrogram obtained from the short-time Fourier transform, $|S|$ denotes its magnitude, and F_s is the sampling

frequency. The quantity S_{dB} is used as a normalized spectrogram-power metric expressed in dB. It is not intended as a calibrated power spectral density. Since the normalization factor F_s^2 is constant for all time-frequency bins and all experiments, it introduces only a constant offset in the logarithmic domain. This offset cancels when computing the proposed max-minus-median metric. The normalization ensures that the resulting values are expressed in a consistent relative scale, allowing comparisons across the controlled experimental conditions in this study.

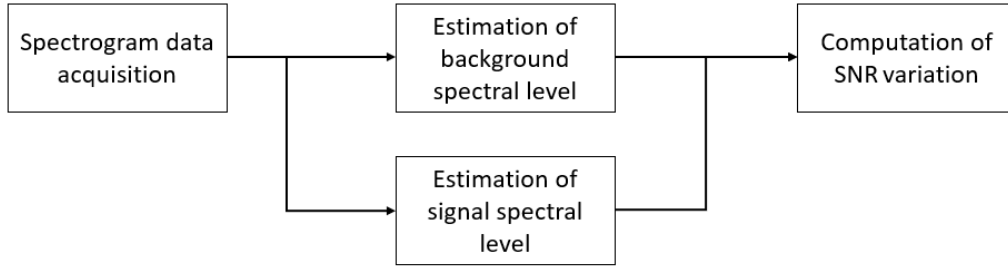


Figure no. 3: *Diagram for estimation of SNR variation*
(Source: Authors' own conception)

For each time window of the spectrogram (i.e., each column of S_{dB}), the proposed method computes a relative SNR-related indicator using simple statistical measures applied across the frequency bins. Specifically, the dominant spectral component is estimated as the maximum value:

$$S_{sig}(j) = \max(S_{dB}(:, j)) \quad (2)$$

while the background spectral level is estimated as the median value:

$$S_{background}(j) = \text{median}(S_{dB}(:, j)) \quad (3)$$

where j indexes the time window.

The use of the maximum operator for signal estimation is justified by the narrowband nature of the analyzed signals (sinusoids or chirps), whose energy is concentrated in a limited number of frequency bins. Although spectral leakage may distribute some energy to adjacent bins, this effect is neglected to maintain a

simple and computationally efficient formulation, without significantly affecting the estimation of SNR variations. However, under the assumptions considered in this work, this simplification remains acceptable for the proposed spectrogram-domain SNR indicator.

The median operator is used to estimate the background level, as we assume that most frequency bins are dominated by noise rather than signal components. Moreover, it provides robustness against outliers, including strong signal components and occasional low-power artifacts, recommending it as a reliable estimator of the background noise floor in relatively clean electromagnetic environments. In dense electromagnetic environments containing multiple simultaneous emitters or strong interference components, the median level may increase,

reducing the estimated contrast between the signal and the background.

From a signal-processing perspective, both the maximum and median operators used in the proposed method belong to the broader class of order-statistics filters, which estimate representative values based on the ordered distribution of spectrogram amplitudes within each STFT column. The median operator corresponds to the 50th percentile of the spectral distribution and was selected because, under the assumptions considered in this study, most frequency bins are dominated by background noise while only a limited number contain significant signal energy. Consequently, the median provides a robust estimate of the background spectral level while remaining relatively insensitive to isolated spectral peaks produced by the signal. In dense electromagnetic environments containing multiple simultaneous signals or interference, the spectral distribution may become asymmetric or partially occupied by non-noise components, potentially biasing the median estimator upward. Under such conditions, alternative percentile-based estimators (e.g. lower-order quantiles) may provide improved robustness by better approximating the underlying background noise floor. Therefore, the use of the median in the present work should be interpreted as a practical choice corresponding to relatively sparse and weakly perturbed spectrogram environments rather than as a universally optimal order-statistics estimator.

Based on these estimates, the relative SNR-metric for each time window can be expressed (up to a constant offset) as:

$$SNR_{est}(j) = S_{sig}(j) - S_{background}(j) \quad (4)$$

SNR_{est} represents a relative SNR-related indicator expressed in dB, quantifying the contrast between the dominant spectral component and the median background level within each

spectrogram column. Therefore, the proposed quantity should not be interpreted as a calibrated SNR estimate obtained from integrated signal and noise powers over explicitly defined frequency bands but rather a spectrogram-based estimated SNR. At low SNR values, the peak spectral component contains a non-negligible contribution from noise, which may bias the proposed estimator and reduce linearity. However, this approach is sufficient for tracking relative SNR variations over time in narrowband spectrogram representations.

If the signal bandwidth increases significantly, as in wideband modulations or rapidly varying chirp signals, the signal energy becomes distributed over a larger number of frequency bins. In such situations, the maximum operator captures only the strongest spectral component rather than the total signal energy, which may reduce the sensitivity and linearity of the proposed metric. of the proposed metric.

One should note that the proposed metric also depends on the selected STFT parameters, including window length, overlap, FFT size, and window type, because these parameters influence spectral concentration and leakage. In the present study, all experiments were performed using fixed STFT parameters to ensure consistent comparisons across signal configurations. In addition, the algorithm is intended to work on spectrogram values directly so we assume that the spectrogram was a priori obtained.

The proposed working algorithm was evaluated through a series of controlled experiments designed to assess its stability and sensitivity with respect to signal parameters and noise levels, as well as its ability to accurately track SNR variations. For all experiments, the amplitudes and frequencies are consistent with the audio range, although the results could be extended to other domains as well.

Table no. 1*Definition and main parameters of the experimental runs*

Parameter	Experiment 1	Experiment 2	Experiment 3
Input signal	sine wave	linear chirp	linear chirp
Signal equation	$s(t) = A \sin(2\pi f_0 t + \varphi_0)$	$s(t) = A \sin(2\pi (f_0 + \Delta f \cdot t) t + \varphi_0)$	
Amplitude	$A = 0.1$ up to 1		
Frequency	$f_0 = 100$ up to 8500 Hz		
Initial phase	$\varphi_0 = 0$ up to $\pi/2$ rad	$\varphi_0 = 0$	
Sweep rate	-	$\Delta f = 100$ Hz/s	$\Delta f = 700$ Hz/s
AWGN	constant at each run (for each combination of input signal parameters)		

For the implemented MATLAB prototype, the total processing time for a 10-second signal realization sampled at 48 kHz was approximately 40 ms on a standard desktop computer. The computational complexity is dominated by the STFT computation, while the proposed max–median estimator introduces negligible additional processing cost.

3. Results and Discussion

The results corresponding to the sinusoidal input signal are presented in

Figures no. 4 and no. 5. Figure no. 4 shows the dependence between the simulated SNR and the estimated quantity (SNR_{est}) for all combinations of amplitude, frequency, and phase. A clear linear relationship is observed over the entire SNR range, confirming that the estimator preserves SNR variations independently of the signal parameters. The computed correlation coefficient is very close to 1 ($\rho = 1 - 1.5 \cdot 10^{-6}$), indicating a near-perfect linear dependence.

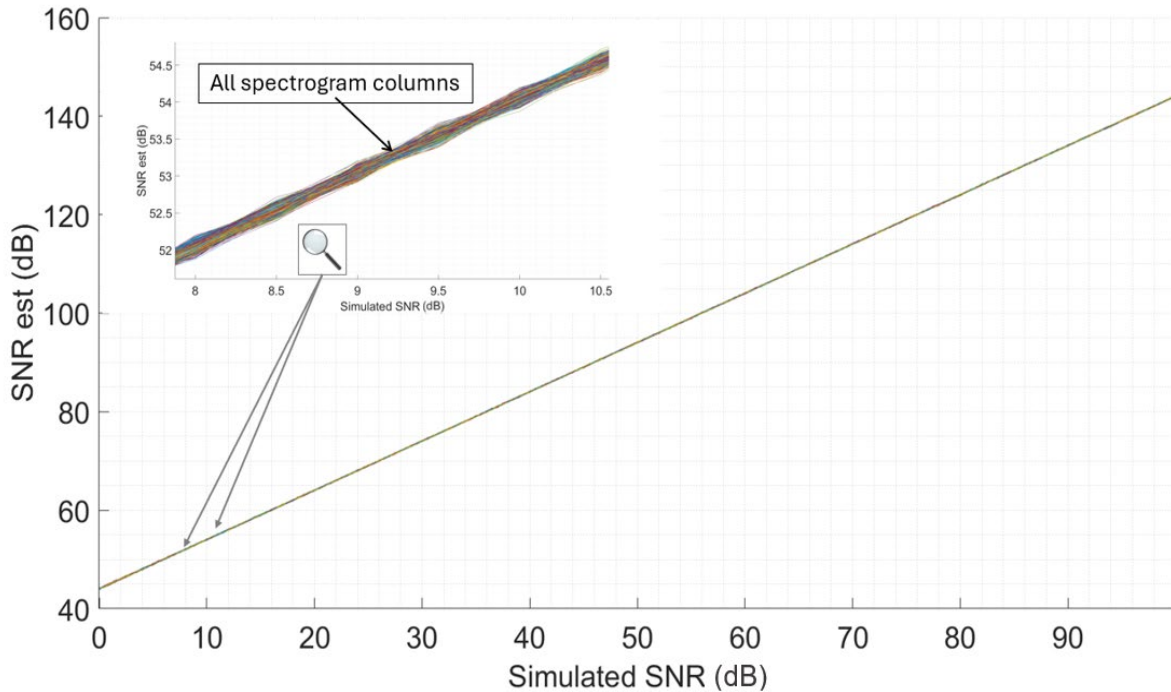


Figure no. 4: *Simulated versus estimated SNR for experiment 1*
(Source: Authors' own conception)

It is important to note that the estimated quantity (SNR_{est}) does not coincide directly with the input SNR but is instead affected by a constant offset. This behavior is expected and can be explained by the proposed metric dependence on the spectral SNR. In the time domain, the input SNR is defined based on the ratio between signal and noise power over all samples. In contrast, within the spectrogram representation, the noise energy is distributed approximately uniformly across the STFT frequency bins, while the signal energy may remain concentrated within a smaller subset of bins. As a result, when estimating SNR from the spectrogram, the signal component appears relatively stronger compared to the noise floor, leading to a systematic increase in the estimated spectral SNR, effect known as STFT processing gain. For a representation using an N length STFT, the STFT processing gain (G_p) can be approximated as (Kester, 1991):

$$G_p[\text{dB}] \approx 10\log_{10}(N/2) \quad (5)$$

Correspondingly, if N is doubled the bin spacing (Δf) is halved and the noise floor is reduced by 3 dB. In addition to the processing gain, the spreading of the signal energy through the STFT frequency bins also affects the proposed metric. Let N_{sig} denote the effective number of frequency bins significantly occupied by the signal

energy. For strictly narrowband signals, such as sinusoids, N_{sig} is very small while for signals with time-varying frequency content, such as chirps, the energy spreads over a larger number of bins. Most practical signals generally occupy more than one frequency bin due to finite frequency resolution, spectral leakage, modulation bandwidth, or nonstationary behaviour. Therefore, the effective peak prominence is reduced by an approximate spreading loss (L_{spread}), defined by:

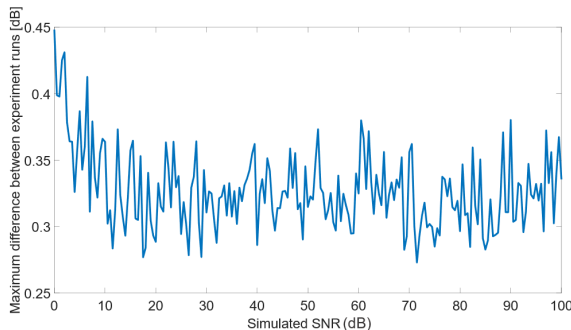
$$L_{\text{spread}}[\text{dB}] \approx 10\log_{10}(N_{\text{sig}}) \quad (6)$$

Accordingly, the spectral-domain SNR (SNR_{spec}) accounting for both processing gain (G_p) and spreading loss (L_{spread}) can be approximated as:

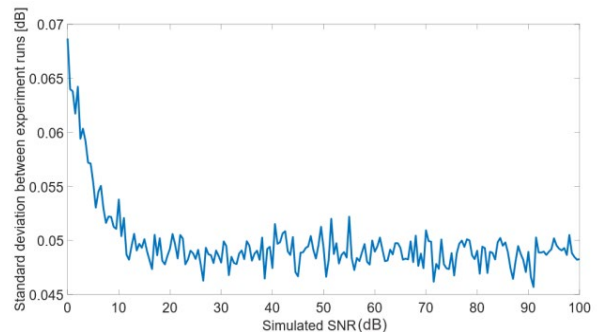
$$\text{SNR}_{\text{spec}}[\text{dB}] \approx \text{SNR}_{\text{input}}[\text{dB}] + G_p - L_{\text{spread}} = \text{SNR}_{\text{input}}[\text{dB}] + 10\log_{10}\left(\frac{N}{2N_{\text{sig}}}\right) \quad (7)$$

which explains both the presence of a constant offset and its dependence on the signal type.

Figure no. 5(a) illustrates the maximum difference between experiment runs for identical SNR values. In the entire simulated SNR (0-100 dB), this difference remains below approximately 0.5 dB, showing that variations in amplitude, frequency, and phase have a limited impact on the estimator.



(a)



(b)

Figure no. 5: (a) Maximum difference between experiment runs and (b) standard deviation between experiment runs – experiment 1
(Source: Authors' own conception)

Figure no. 5(b) shows the standard deviation of the estimates across runs, which remains low, typically around 0.05-0.1 dB. This confirms the stability of the estimator for stationary narrowband

signals. Additionally, variations across spectrogram time windows within the same run are significantly smaller, indicating high temporal consistency.

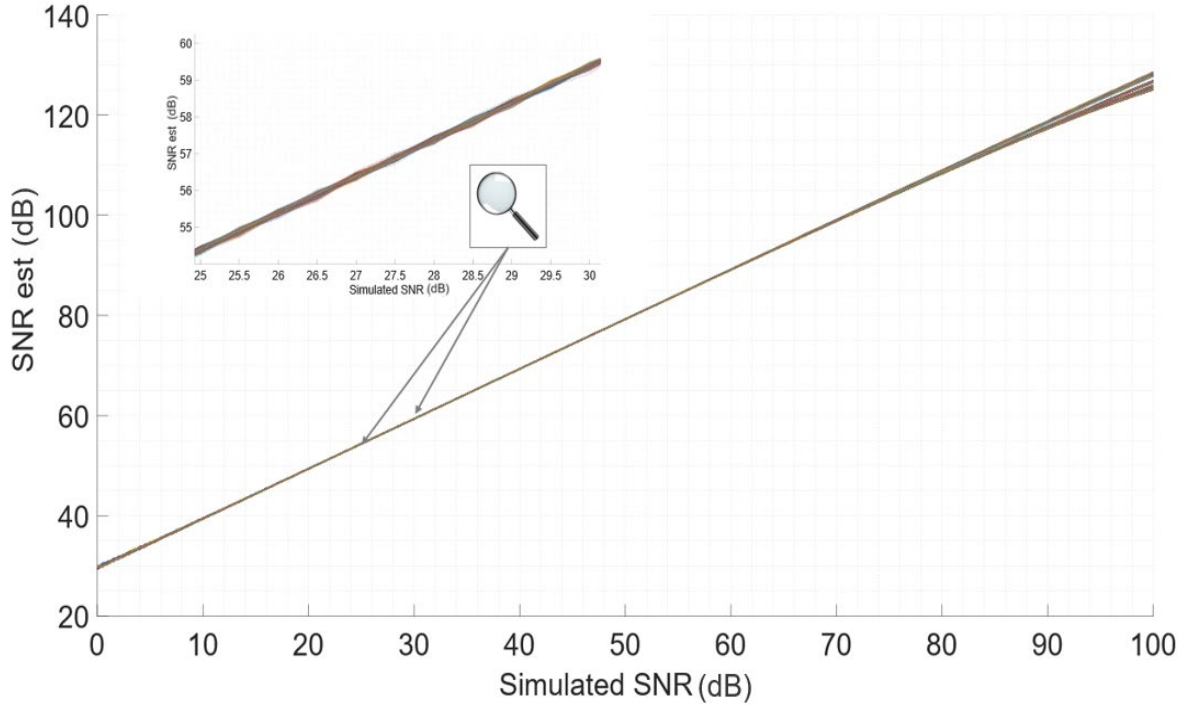
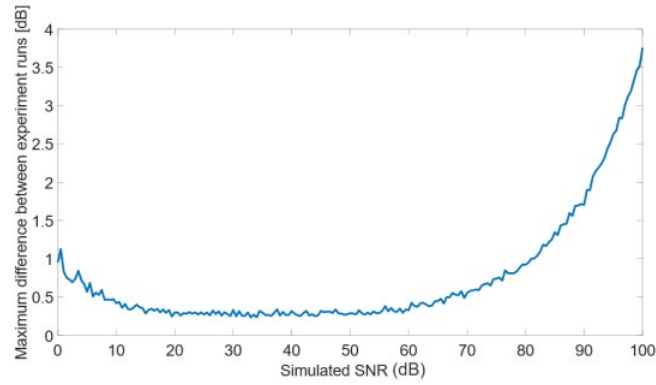


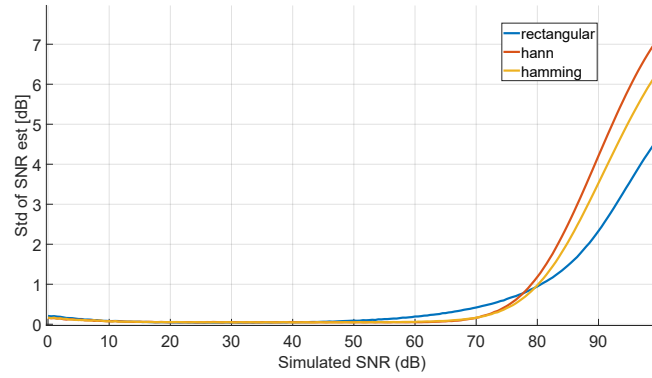
Figure no. 6: *Simulated versus estimated SNR for experiment 2*
(Source: Authors' own conception)

The results for the first chirp configuration (experiment 2) are shown in Figures no. 6 and no. 7. As in the sinusoidal case, Figure no. 6 demonstrates a strong linear relationship between the simulated SNR and the estimated values, with a correlation coefficient close to unity ($\rho = 1 - 10^{-4}$). Compared to results in experiment 1, higher nonlinearities can be observed at both low and very high SNR values. Even though the cause of these effects is the same, the differences observed between the sinusoidal and chirp cases are primarily due to the distinct spectral characteristics of the two signal types. A

sinusoidal signal is stationary, and its energy is concentrated in a single frequency bin (or a very small number of bins) for all time windows. As a result, the maximum operator provides a stable estimate of the signal power, and the separation between signal and noise remains consistent across both time and frequency. In contrast, a chirp signal is non-stationary, resulting in the signal energy being distributed along a frequency trajectory rather than confined to a fixed bin, reducing the sharpness of the maximum value indicator, as indicated in eq (Figure no. 7).



(a)



(b)

Figure no. 7: (a) Maximum difference between experiment runs and (b) standard deviation between experiment runs – experiment 2
(Source: Authors' own conception)

Figure no. 7(a) presents the maximum difference between experiment runs. The variability remains below approximately 0.5 dB in the 10-60 dB range, like the sinusoidal case, indicating that the method is robust to variations in chirp parameters such as amplitude and frequency. However, for higher SNR values, the spread increases more noticeably compared to the sinusoidal case, reflecting the increased influence of spectral leakage due to the continuous frequency variation of the chirp. To evaluate the influence of windowing on these effects, additional simulations were performed using Hann and Hamming windows. The results are presented in Figure no. 7(b), which compares the standard deviation of the estimated $SNR_{est,dB}$ metric for the three window types. Overall, the standard deviation shown in Figure no. 7(b) remains around

0.1 dB across most of the SNR range, confirming consistent estimation performance. The slightly higher dispersion compared to the sinusoidal case is expected and explained in the paragraphs above. The rectangular window produced the lowest variability at very high SNR values in the present implementation, while Hann and Hamming windows exhibited a steeper increase in estimator variance above approximately 80 dB. It should also be noted that the proposed estimator is intended to operate directly on existing spectrogram representations, potentially without access to the original IQ or time-domain data. In such scenarios, the STFT window type has already been applied during spectrogram generation and cannot be modified afterward. Therefore the modification of the window type is possible in controlled conditions only.

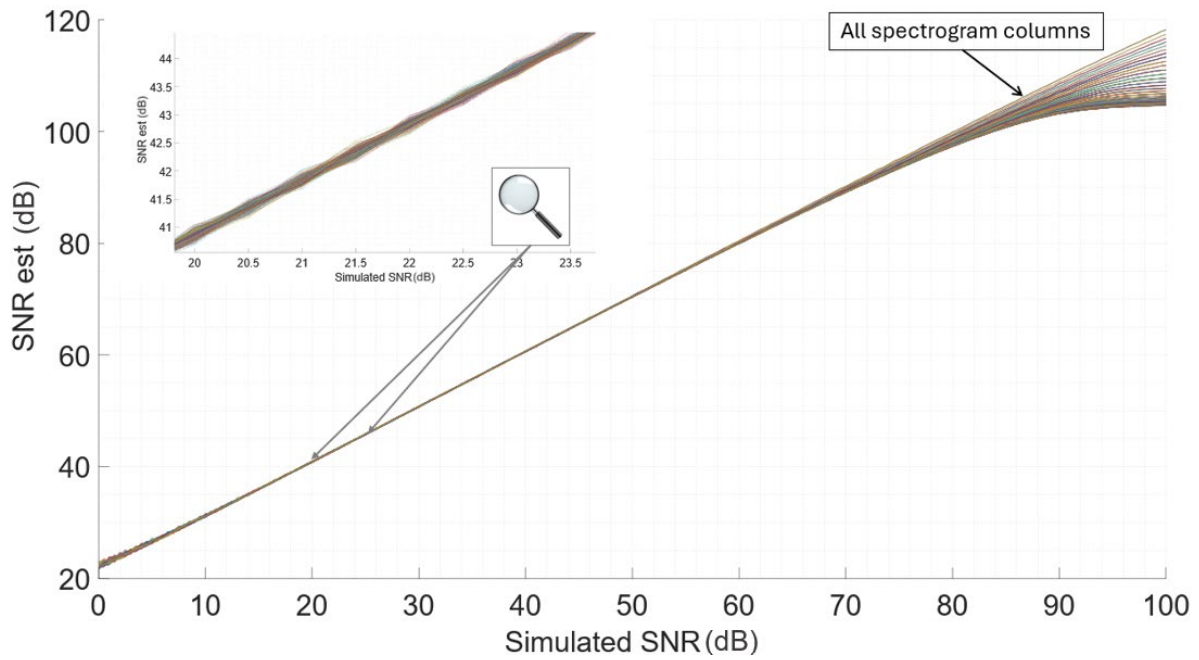


Figure no. 8: *Simulated versus estimated SNR for experiment 3*
(Source: Authors' own conception)

The results for the second chirp configuration are presented in Figures no. 8 and no. 9. Again, Figure no. 8 confirms the persistence of a strong linear relationship between the simulated and estimated SNR values, with a correlation coefficient close to 1 ($\rho = 1 - 2.5 \cdot 10^{-3}$). In this second chirp configuration, the effect is further accentuated in the high SNR range by the higher frequency sweep rate (700 Hz/s compared to 100 Hz/s), which causes the signal energy to spread over a larger number of frequency bins within each time window. This reduces the concentration of energy and decreases the sharpness of the maximum-based estimator, leading to increased deviations from linearity.

For this experiment, Figure no. 9(a) shows that the maximum difference

between experiment runs remains below approximately 1 dB in the 10-60 dB range, slightly higher than in the previous experiments. This increase reflects the combined effect of parameter variations and the dynamic frequency content of the chirp signal. As in the previous cases, the variability increases at higher SNR values due to reduced noise contribution.

Figure no. 9(b) indicates that the standard deviation remains around 0.1 dB, confirming that the estimator retains good statistical stability even under more challenging signal conditions. As observed in the previous experiments, the variation across spectrogram time windows within the same signal remains significantly lower than the variation across different runs.

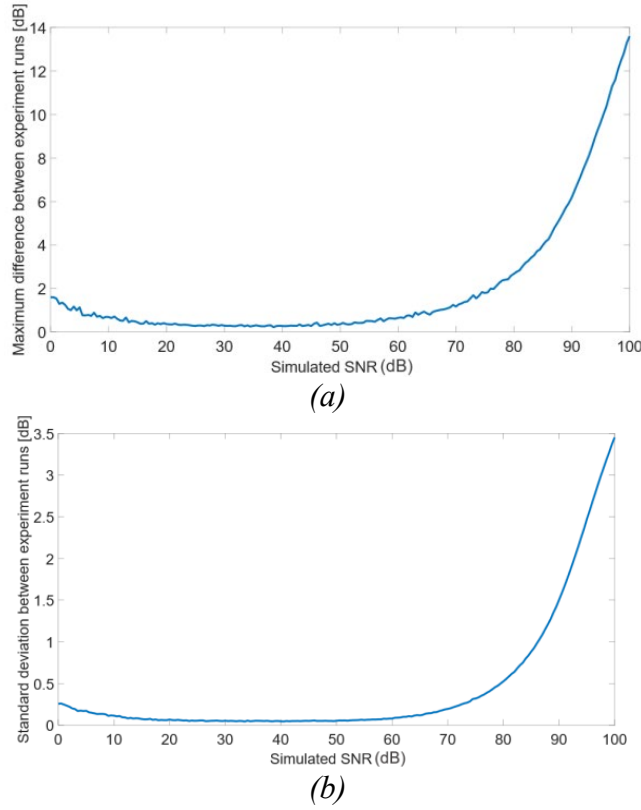


Figure no. 9: (a) *Maximum difference between experiment runs* and (b) *standard deviation between experiment runs – experiment 3*
(Source: Authors' own conception)

5. Conclusions

The paper presents a low computational complexity method for determining SNR variations in spectrogram representations of narrowband signals. The proposed approach relies on simple statistical estimators applied to spectrogram values, enabling the estimation of signal and noise levels without requiring access to the original time-domain signal.

The experimental results demonstrate a strong linear relationship between the estimated metric and the reference SNR across all tested configurations, including both sinusoidal and chirp signals, with correlation coefficients close to unity. The proposed estimator exhibits low variability with respect to signal parameters such as amplitude, frequency, phase, and frequency slope, with differences between experiment runs remaining within sub-dB levels for the most relevant SNR ranges.

Nonlinearities were observed at very low and very high SNR values. At low SNR, these are caused by reduced separability between signal and noise components, while at high SNR, they are mainly due to spectral leakage, finite frequency resolution, and numerical precision effects. These effects are more pronounced for chirp signals, particularly for higher frequency sweep rates, due to the spreading of signal energy across multiple frequency bins. However, within the practical SNR range (typically below 60-70 dB), the method maintains a highly linear behavior and stable performance.

A constant offset between the input SNR and the spectrogram-based estimate was identified and explained through the processing gain inherent to time-frequency representations. This offset depends on the signal type and spectral characteristics but does not affect the ability of the method to

track SNR variations, which is the primary objective.

Overall, the proposed method demonstrates computational simplicity and consistent behaviour for evaluating SNR variations in both stationary and non-stationary narrowband signals. Its low computational cost and sole reliance on spectrogram data make it suitable for real-time applications such as interference detection, spectrum monitoring, and signal quality assessment.

Future work may focus on compensating for the offset to enable

absolute SNR estimation, extending the approach to wider-band signals, and validating the method on real-world datasets and hardware implementations.

Author Contributions

Conceptualization, M.N. and A.S.; methodology, M.N.; validation, M.N. and A.S.; formal analysis, M.N. and A.S.; investigation, M.N.; writing—original draft preparation, M.N.; writing—review and editing, A.S. All authors have read and agreed to the published version of the manuscript.

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