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Adaptive Transformation Algorithm for Detecting Parameters of a Sinusoidal Signal

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Abstract. The paper presents an adaptive transformation algorithm developed for detecting the parameters of sinusoidal signals under noisy and nonstationary disturbances. The proposed method provides estimation of the signal's amplitude, frequency, and phase with increased accuracy through dynamic adjustment of transformation parameters according to the current characteristics of the input. This approach makes it possible to significantly improve the robustness and reliability of estimates compared with traditional spectral analysis methods, especially when processing signals with time-varying parameters. The presented numerical simulation results confirm the effectiveness of the proposed algorithm in the analysis of sinusoidal signals of various types and parameters.

Keywords: Adaptive transformation; Sinusoidal signal; Parameter estimation; Frequency detection; Amplitude estimation; Phase estimation; Signal processing; Adaptive algorithms.

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1. Introduction

Sinusoidal signals are widely encountered across many fields of science and engineering, including telecommunications, radar, navigation, medical diagnostics, and vibration analysis. Accurate estimation of their parameters—amplitude, frequency, and phase—is a key step in solving problems of signal detection, identification, and filtering. In practical conditions, analysis is complicated by noise, limited measurement resources, and possible nonstationarity of parameters caused by frequency drift, amplitude modulation, or changes in the propagation medium. This creates the need for algorithms capable of providing stable and accurate parameter estimation under uncertainty.

Classical spectral analysis methods, such as the Fourier transform and its modifications, demonstrate high efficiency when dealing with stationary signals. However, when signal parameters vary over time or when observations are subject to strong noise interference, the performance of such methods decreases significantly. Limitations associated with fixed spectral resolution and the lack of mechanisms for adapting to the current signal structure require the development of new approaches that can dynamically adjust to incoming data.

In recent years, adaptive algorithms that use information about the current state of the signal to modify their internal parameters have attracted increasing interest. Such methods can respond more flexibly to variations in time–frequency structure and provide improved estimation quality compared to traditional approaches. Adaptive transformations that combine elements of statistical filtering, optimization, and spectral analysis represent a promising research direction in digital signal processing.

This paper proposes an adaptive transformation algorithm designed to detect the parameters of a sinusoidal signal under noisy and nonstationary conditions. The core idea of the approach is the dynamic adjustment of computational scheme parameters based on the current characteristics of the input signal. This makes it possible to increase the accuracy of amplitude, frequency, and phase estimation, as well as to improve the algorithm's robustness to noise. Simulation results are presented to demonstrate the effectiveness of the developed method in analyzing sinusoidal signals with various parameters and interference levels.

2. Overview of Time-Frequency Analysis Methods

Time–Frequency Analysis (TFA) comprises a set of techniques aimed at studying signals with time-varying spectral characteristics. Unlike the classical stationarity model, which assumes an invariant spectrum over the entire observation interval, TFA enables the description of local frequency components and the dynamics of their evolution. Modern approaches to time–frequency analysis can be broadly classified into linear methods, quadratic methods, reassignment techniques, and adaptive methods.

NI's LabVIEW platform provides an extensive set of time–frequency tools, including Adaptive Transform VI, Adaptive Expansion VI, and Adaptive Spectrogram VI.

These tools are based on adaptive signal decomposition into a set of Gaussian chirplets with arbitrarily chosen time and frequency centers, varying durations, and individual frequency modulation rates. In Adaptive Spectrogram VI, the resulting time–frequency distribution is formed by summing the auto-terms of the Wigner–Ville distributions (WVD) of the detected chirplets, enabling high energy concentration while suppressing cross-term distortions [1-2,5].

Adaptive Transform VI implements an adaptive chirplet decomposition of the observed signal $x(t)$.

$$x(t) \approx \sum_{k=1}^{D} A_k \; h_k(t; \theta_k), \tag{1}$$

where

$\theta_k = \{t_{0,k}, f_{0,k}, \sigma_k, c_k, \varphi_k\}$— denotes the parameters of the k-th chirplet,

$A_k \in \mathbb{C}$— is the complex amplitude,

D— is the number of selected atoms.

Each chirplet is defined by the expression:

$$h(t; \theta) = \exp\left(-\frac{(t-t_0)^2}{2\sigma^2}\right) \; \exp\{j(2\pi f_0(t-t_0) + \pi c(t-t_0)^2 + \varphi)\}, \tag{2}$$

where σ controls the window duration, $f_0$is the local frequency, and c is the linear frequency modulation rate (chirp rate). This form corresponds to Gaussian-windowed linear chirp models used in LabVIEW Time–Frequency Analysis (TFA) [2-4].

For fixed parameters θ_k, the problem of estimating the amplitudes reduces to minimizing the approximation error:

$$\min_{\{A_k\}} \; \| \, x(t) - \sum_{k=1}^{D} A_k \, h_k(t) \, \|_2^2, \tag{3}$$

In discrete form, the solution takes the following form:

$$\mathrm{A} = (\mathrm{H}^H \mathrm{H})^{-1} \mathrm{H}^H \mathrm{x}, \tag{4}$$

where H is the matrix whose columns contain the samples of $h_k(t)$. Adaptive Transform VI returns the estimated amplitudes in the chirplet info/amplitude structure.

3. Adaptive Spectrogram (Time-Frequency Representation)

In Adaptive Spectrogram VI, the resulting time–frequency representation (TFR) is calculated as the sum of the auto-terms of the Wigner–Ville distribution (WVD) of all detected chirplets.

$$T_x(t,f) = \sum_{k=1}^{D} \mathrm{WVD}\,(h_k)(t,f), \tag{5}$$

which provides high time–frequency resolution with complete elimination of cross-terms, since the Wigner–Ville distribution is computed separately for each component. Thus, the Adaptive Spectrogram combines the advantages of adaptive decomposition and quadratic distributions without the interference effects characteristic of the WVD [3-4].

4. Results

To verify the performance of the adaptive transformation algorithm, a test signal was generated consisting of two sinusoidal components with frequencies of 30 Hz and 40 Hz, with added noise of amplitude 1. Figure 1 shows the original observation. The signal is characterized by significant noise fluctuations, which makes the task of extracting the frequency components nontrivial.

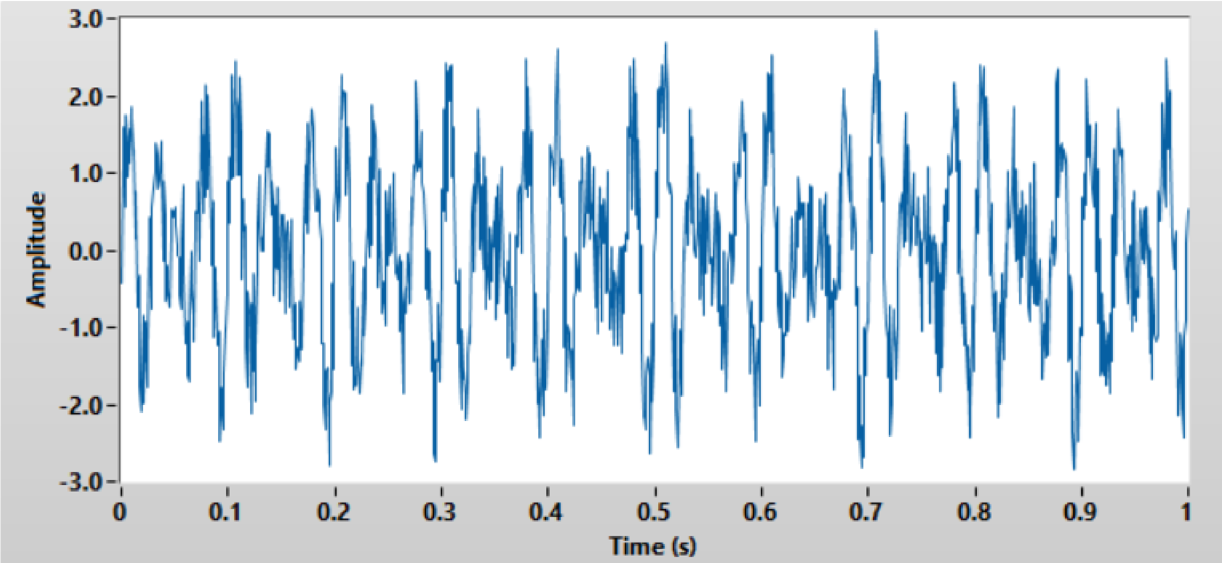

Fig.1. Original observation.

The adaptive algorithm successfully identified both harmonic components present in the signal. The detected frequencies were:

- 30.04 Hz
- 40.02 Hz

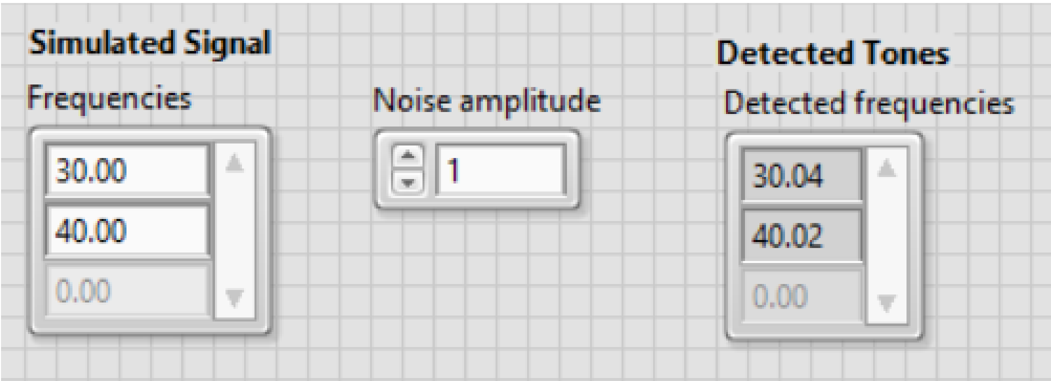

Fig.2. Simulated and reconstructed signals' frequencies.

which indicates high frequency estimation accuracy even under a significant noise level. The deviation from the true values does not exceed 0.1%, which is consistent with the accuracy level reported for adaptive chirplet decomposition algorithms in the literature.

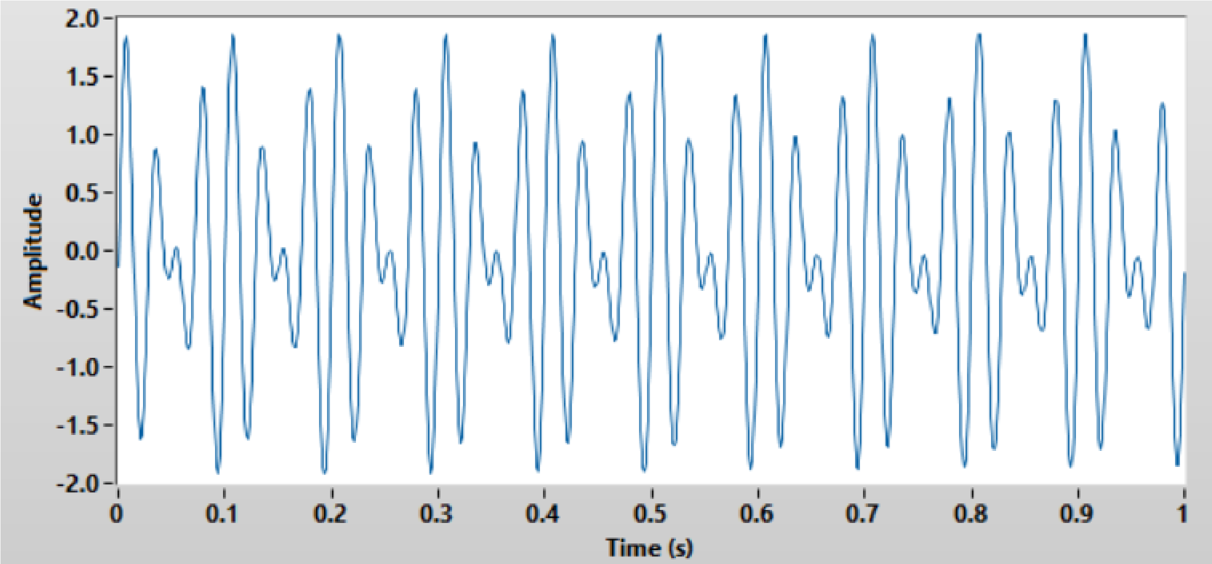

Fig.3. Reconstructed signal.

Figure 3 shows the reconstructed signal obtained by summing the detected harmonic components. the reconstructed signal:

- exhibits clear periodicity,
- is almost completely free of the noise component,
- reproduces the dynamics of the original sinusoidal components.

A comparison of the original and reconstructed signals demonstrates the method's ability to effectively suppress noise and accurately estimate frequency components, confirming its suitability for analyzing nonstationary and noisy data.

5. Conclusions

The conducted simulations confirm the effectiveness of the proposed adaptive transformation algorithm for detecting the parameters of sinusoidal signals under significant noise conditions. The algorithm successfully identified the frequency components corresponding to the original sinusoids, achieving high estimation accuracy (error below 0.1%). This level of precision demonstrates the capability of adaptive chirplet decomposition to adjust to the signal structure and suppress noise components effectively. This is further supported by the signal reconstruction results: the denoised signal preserves the waveform and amplitude–frequency characteristics of the original components.

The obtained results are consistent with the well-known advantages of adaptive analysis methods, particularly chirplet-based representations and adaptive spectrogram techniques, which provide high time–frequency energy concentration and eliminate cross-interference terms typical of quadratic time–frequency representations. Therefore, the proposed method can be recommended for applications involving the processing of noisy and nonstationary signals, including vibration diagnostics, radar systems, condition monitoring, and spectral analysis of complex time-varying processes.

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