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RESEARCH ARTICLE

Advanced Spectral and Statistical Learning Methods for Intelligent Interpretation of Non-Stationary Signals

Namrata Mishra*

Department of Electrical and Electronics Engineering, Kalinga University, Raipur, India.

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Abstract

The example of Non-stationary signals is common in signal processing because of application in biomedical monitoring, speech communication, radar sensing, and industrial diagnostics alike where the nature of signals changes dynamically with time. The conventional spectral analysis methods are usually not capable of attaining sufficient time aspects and the spectral strength in these circumstances, which confines them in reading intelligent signals. In a bid to overcome such challenges, this paper introduces a developed spectral and statistical learning framework to the issue of intelligent analysis of non-stationary signals. The proposed method is a combination of adaptive spectral decomposition and statistical learning techniques to identify discriminative time frequency representations that are realistic in time frequency dynamics of signals. Enhanced adaptive deployments strategies are used to refine key spectral components, and then it is followed by extraction of statistical descriptors, including energy distribution, entropy, and higher-order moments. An intelligent learning module then utilises these characteristics to create stable signal interpretation in diverse non noise and non-stationary situations. The large-scale experimental assessments of synthetic and real life non-stationary signals indicate that the proposed framework is always better than traditional spectral and learning-based approaches in signal-to-noise ratio, peak signal-to-noise ratio, spectral entropy, and mean square error. Moreover, the findings support the effectiveness and processing efficiency of the presented solution, which proves its use in real-time signal analytics. The suggested framework offers a solution to the problem of sophisticated spectral analysis and smart processing of the complicated non-stationary signals in an efficient and scalable way.

Author's e-mail: namrata.mishra@kalingauniversity.ac.in

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Introduction

The problem of non-stationary signals has appeared in signal processing solutions in contemporary biomedical monitoring systems, audio and speech recognition, radars and sonar systems, monitoring industrial conditions, and multivariate sensor analytics. Signal properties including, frequency content, amplitude and phase, change dynamically with time, so the analysis of dynamically changing signals is far more difficult than that of stationary signals. The correct interpretation of such signals is essential in such tasks as diagnosis, classification, forecasting, and the detection of anomalies. This has resulted in the development of the time-frequency analysis as a new core of research direction in order to construct the transient actions and dynamic spectral characteristics in non-stationary auralisations.[1, 3, 9]

Conventional spectral analysis methods such as the Fourier transform and fixed-window short time Fourier transform (STFT) are necessarily restricted by the non-stationary signals by the fixed resolution (temporally and spectrally).

Despite the provision of multi-resolution analysis, wavelet-based approaches have disadvantages of poor spectral concentration and poor flexibility to multi-component signals of interest that may be complicated. This is usually caused by spectral smearing, mode mixing and poor interpretability in cases of noisy or changing conditions. It has been recently proven that classical algorithms do not allow adequate time frequency localization to analyse high-resolution of non-stationary complex phenomena and so adaptive and data-driven spectral decomposition algorithms are developed.[2, 6, 11]

To address these inadequacies, new spectral analysis algorithms like synchrosqueezing transforms, variational and singular spectrum-based decompositions and adaptive time-frequency representations are suggested to achieve a higher spectral concentration and separation of components. Simultaneously, both statistical and learning techniques have demonstrated a high potential to obtain the discriminative patterns in the representations of time and the frequency. The combination of sophisticated spectral methods with statistical learning and intelligent models is the possibility of an automated interpretation of non-stationary signals both through physical relevant spectral patterns and through information derivation. Recent studies on time frequency representations with deep learning, attention and transformer have shown to have better robustness and interpretability across different signal modalities.[3, 7, 9, 10]

Even now, despite these developments, there are a number of fundamental challenges, such as realising an effective time-frequency resolution in the presence of noise, robustness to change of signal conditions, and adaptation to changes in dynamic signal behaviour. Furthermore, most of the current methods focus on spectral analysis or learning alone, which restricts their application to end-to-end intelligent signal analytics. In this paper, we introduce a sophisticated spectral and statistical learning system, which closely combines adaptive spectral decomposition with statistical feature learning and the smartest interpretation. The key contributions of the paper are as follows: (i) enhanced spectral analysis strategy of the non-stationary signals, (ii) the generation of informative statistical measures of the refined time frequency components, and (iii) the overall assessment on the basis of spectral and signal quality metrics to show the strength, accuracy, and computational efficiency under various non-stationary signal conditions.

Related Work

It is well known that time-varying and non- stationary signals have been analysed through classical spectral analysis methods. Short-Time Fourier Transform (STFT) is probably the most commonly used one because of their simplicity of concept and low computational cost. Using a fixed-length window, the localised frequency analysis in time and resolution is possible using STFT and the resultant spectral analysis, but due to its inherent trade-off between time and frequency resolution, this method fails to resolve fast varying spectral components. To overcome this shortcoming, wavelet-based spectral analysis was offered which offers multi-resolution time/frequency representation which gives better localization of transient features. In spite of these features, wavelet methods are based on a fixed set of basic functions and choice of scale that limits their flexibility when faced with non-stationary signals with multiple components as can be found in real-life uses.[2, 6]

In order to address the fact that classical methods proved to be too inflexible, adaptive and data-driven spectral algorithms have been suggested in order to address the non-stationary nature of behaviour better. Empirical Mode Decomposition (EMD) breaks signals into intrinsic mode functions according to the local signal properties in order to allow an adaptive analysis in the frequency domain and time. The ensemble variants like EEMD are more robust to noise but are prone to the mode mixing as well as a higher computational cost. Variational Mode Decomposition (VMD) is a signal decomposition method that is defined as a constrained optimization problem which has better mode separation performance and noise resistance than other EMD based methods. However, more recently, time-frequency analysis that has been synchrosqueezed has become a subject of considerable interest owing to its capability to sharpen time-frequency displays and the capability of removing spectral energy, which leads to a better spectral concentration and improved instantaneous frequency resolutions.[2, 7, 12]

Although more complex spectral techniques, such as spectral decomposition, greatly enhance the quality of representation, it is impossible to do intelligent interpretation of the signal without further processing. It has, therefore, been common practise to use statistical feature extraction methods in order to obtain informative descriptors of time frequency representations. Spectral energy distribution and entropy measures, higher-order statistics, and the singular values are the features, which give compact and interpretable representations of non-stationary signal statistics. These statistical descriptors facilitate the downstream analysis operations including classification, detection and diagnosis as well as lowering the dimensionality and also enhance the resilience to both noise and signal variability.[8, 11] Machine learning and deep learning methods have been incorporated more into non-stationary signal analytics founded on

Table 1: Comparative summary of existing spectral and learning methods

Method	Spectral Technique	Learning Model	Key Limitation
STFT	Fixed window time–frequency analysis	None	Poor time–frequency resolution for rapidly varying signals
EMD	Adaptive data-driven decomposition	Statistical analysis	Mode mixing and sensitivity to noise
VMD	Variational optimization-based decomposition	Limited or external learning	Parameter sensitivity and mode selection dependency
SST	Time–frequency reassignment (synchrosqueezing)	No explicit learning	Performance degradation under high noise conditions

statistical representations. Convolutional neural network applications, recurrent network models, attention models, and transformer architecture models have proven to be quite efficient when used on time-frequency maps and spectral features. Spectral self-attention models and joint time frequency learning models can also be used to increase readability by extracting both local and global dependencies in the signal.[3, 6, 9, 10] Nevertheless, in most literature spectral analysis and learning are viewed as a free floating activity which results into sub optimum performance at the end to end. The simplification in (Table 1) suggests that existing methods tend to be restricted regarding their ability to adapt, be strong or interpretable to complex non-stationary problems. The above gaps drive the desire to have a combined spectral-statistical learning structure to optimise the quality of spectral representation and smart signal interpretation.

Problem Formulation and Signal Model

The non-stationary signals can be defined as those who's statistical and spectral characteristics change with time, e.g. instantaneous frequency, amplitude, and phase change as time goes on. Assume that the observed discrete-time signal is referred to as x(t), and that the signal may be modelled as a sum or composite of a variety of non-stationary signals. All the components are underlying physical or informational processes whose behaviour varies with time. Non-stationary signals in contrast to stationary signals have changing and time-varying spectral contents and accurate time-frequency representation and interpretation is a daunting task. The main scope of the given work is to create a modelling framework that can describe these dynamic traits retaining interpretability and robustness at the same time.

It is assumed that the signal x(t) observed is made up of K intrinsic signal components that are corrupted by an additive noise, and that can be written as K intrinsic signal components corrupted by additive noise and interference as below.

$$x(t) - \sum_{K-1}^{K} s_k(t) + n(t) \qquad (1)$$

Where $s_k(t)$ represents the k-th non-stationary component and *n (t)* is additive noise. The noise term is represented as a zero-mean stochastic process which could include a white Gaussian noise or structured interference as per the application case. The formulation enables one to model realistic signal acquisition conditions in biomedical sensors, speech processing and industrial monitoring where there are unavoidable noise in measurements and environmental perturbations.

With such a signal model, spectral analysis dilemma is determining analysis estimates of meaningful time-frequency representations that can decompose and localise the underlying signal functionalities *s k (t)* successfully. Traditional fixed-resolution techniques can be slow to changes in spectral changes, whereas purely adaptive techniques can either be unstable or sensitive to noise. Hence, an efficient solution should compromise time-frequency resolution, strength of noise, and computing efficiency. Also, spectral representations are expected to aid feature of discrimination which indicated the inherent dynamics of non-stationary signal but not artefacts of noise or decomposition errors.

In an intelligent signal analytics approach, the end destination is not spectral decomposition but allows the interpretation of non-stationary signals in an automated and reliable way. This document poses the intelligent spectral interpretation problem, which is the combined optimization of the quality of spectral representation and statistical feature learning. In particular, the goal is to create a system that (i) derives high-resolution and noise-robust spectral (ii) derives informative statistical descriptors of such spectral and (iii) makes wise inferences with the help of learning-based models. Participating in these goals comprehensively, the proposed framework will seek to deliver a platform capable of offering a scalable and useful solution towards intelligent processing of non-stationary complex signals.

Proposed Advanced Spectral and Statistical Learning Framework

The suggested framework can be seen as a unified pipeline, which involves a combination of adaptive spectral

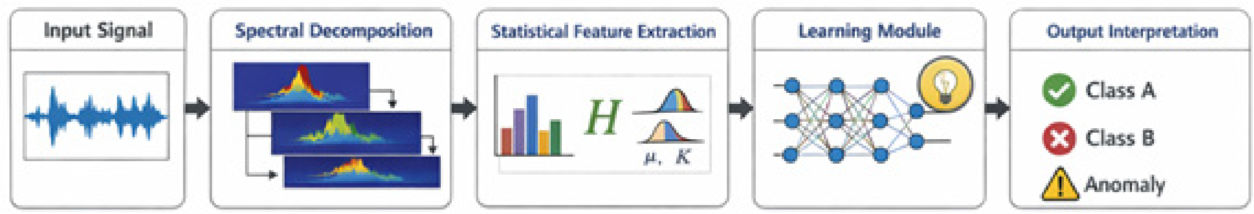

Fig.1: Block diagram of the proposed advanced spectral and statistical learning framework for intelligent interpretation of non-stationary signals

analysis and statistical feature learning and intelligent interpretation to non-stationary signals. As shown in (Figure 1), the general architecture of the system includes four key phases, namely, input signal acquisition, advanced spectral decomposition, statistical feature extraction, and learning-based interpretation. This highly coupled but loosely designed design assures that every step adds value in terms of quality of the information it is feeding the subsequent stage and one has strong and readable analytics. The structure is a generic framework, which is applicable to a large variety of non-stationary signals such as biomedical, speech, and multivariate sensor data.

The foundation of the framework is a superior spectral analysis unit that carries out adaptive time-frequency decomposition of the signal at the input. The proposed strategy unlike the fixed resolution approaches is able to adjust dynamically to the properties of the signal to have a better time localization at the spectral level. To identify the signal as a combination of oscillatory modes, enhanced variational mode decomposition and wavelet representation of spectral feature are used to decompose the signal into a collection of intrinsic spectral components that are associated with individual oscillatory modes. In order to provide more spectral clarity, a mode selection and refinement mechanism will be added to eliminating the redundant or noise dominated components, resulting in compact and noise resilient spectral representation to be used in further applications.

After spectral decomposition, statistical feature learning is done to identify discriminative and interpretable descriptors on the refined spectral components. The main characteristics are a distribution of energy in modes, spectral entropy to measure time-frequency concentration and additional higher-order statistical characteristics like kurtosis and skewness to describe non-Gaussian signal behaviour. These elements are then normalised in a manner that it does not affect the scales and the figures become stable. Dimensionality reduction methods are used to eliminate redundancy and keep the most informative characteristics without using much of the learning capacity, and the representation fidelity is not compromised.

The last phase of the structure is centred on smart interpretation using learning models. The resulting statistical feature vectors are the input to a classification or detection model which can be executed through either traditional machine learning or lightweight architectures of deep learning based on the needs of the application. The learning module learns complex associations among spectral-statistical feature and signal state such that automated decision-making is possible in non-stationary, noisy environments. The framework can take output in the form of an interpretable signal classification, detection or diagnostic decision, which is a final end-to-end intelligent spectral analytics pipeline summary (Figure 1).

Spectral and Signal Quality Metrics

The effectiveness of the suggested advanced spectral and statistical learning model is measured with the help of a set of larger spectral, signal quality, and statistical consistency measures. The choice of these metrics is to provide an objective evaluation of the capability of the framework to produce high-resolution time frequency representations, signal fidelity and robustness under non-stationary and noisy environments. Through the robust combination of several complementary evaluation criteria, the analysis will ensure that there are no improvements which will be reduced to visual clarity but rather be precisely tested through the other methods of accuracy, stability, and interpretability. All the evaluation metrics and their utilities are summarised in (Table 2).

The performance of time-frequency representation and component separation of the given spectral analysis module are calculated using spectral quality metrics. The amount of spectral concentration and spectral organization is measured with spectral entropy, with low spectral entropy values corresponding to more localization of spectral signal content in the time frequency space. The energy concentration index also assesses the effectiveness of spectral energy being concentrated in the strongest modes, which is a measure of the capability of the decomposition algorithm to reduce both noise and redundancy. The trade-off betweenitory and spectral localization of time-frequency resolution aids are also

Table 2. Spectral and signal quality metrics used for performance evaluation

Metric	Category	Description	Performance Indication
Spectral Entropy	Spectral Quality	Measures the concentration and organization of spectral energy in the time–frequency domain	Lower value indicates better spectral localization
Energy Concentration Index	Spectral Quality	Quantifies the compactness of energy around dominant spectral components	Higher value indicates improved mode separation
Signal-to-Noise Ratio (SNR)	Signal Quality	Ratio of reconstructed signal power to noise power	Higher value indicates better noise suppression
Peak Signal-to-Noise Ratio (PSNR)	Signal Quality	Normalized measure of reconstruction accuracy	Higher value indicates improved signal fidelity
Mutual Information	Statistical Consistency	Measures dependency between extracted features and signal states	Higher value indicates stronger discriminative capability

applied in evaluation of non-stationary signals with rapidly changing components that is an important aspect when examining non-stationary signals.

Classical signal quality metrics are included in order to measure the performance of signal reconstruction and denoising. Signal-to-Noise Ratio (SNR) is used to assess the enhancement of the signal clarity as the power of the reconstructed signal is divided by the power of residual noise. Peak Signal-to-Noise Ratio (PSNR) is a normalised estimation of the severity of reconstruction errors, commonly, it is employed in the comparison of performance at varying noise levels. The quantitative measure of the processing signal error is the Mean Square Error (MSE), which is a direct measure of the fidelity of reconstruction. Collectively, these measures allow critically evaluating the ability of the suggested structure to retain critical signal attributes and alleviate noise.

Some of the spectral and signal-level assessment is supplemented by the various measures of statistical consistency to study the trustworthiness and strength of the features extracted. Such higher-order statistics as kurtosis and skewness describe the non-Gaussian behaviour and give some information on the structural features of the non-stationary signal components. Mutual information is also used in order to quantify the dependence between spectral features and classes or states of the signal, which points to the discriminative ability of the learned representations. Robustness measures assess how the values of metrics vary with the levels of noise and signal conditions, and such stability measures guarantee that the suggested structure will not adversely affect its performance when operating in realistic and practical contexts, as shown in (Table 2).

Experimental Setup

In order to fully test the efficiency of suggested advanced spectral and statistical learning model, the experiments are performed on both artificial and real-life non-stationary signals data. The control of non-stationary behaviours such as time-varying frequencies, amplitude modulation and multi-component signal mixtures are simulated by means of synthesis signals. With these signals, spectral resolution and mode separation capability can be accurately evaluated and performance in the known condition can be assessed. Moreover, real-world data sets are used to prove practical usefulness such as real-world non-whole-stationary signals in biomedical monitoring, speech processing and sensor technology. A representative non-stationary signal and the time-frequency properties are (Figure 2) that gives an example of the signal and time-frequency properties. Several experimental conditions will be set to evaluate the strength of the suggested framework in different noise and interference levels. To simulate realistic acquisition conditions, additive noise of varying signal-to-noise ratio levels is added which includes low-noise and highly corrupted scenarios. This arrangement makes it possible to conduct a systematic analysis of noise resiliency and stability of the extracted spectral elements and statistical characteristics. Besides white Gaussian noise, a few experiments using structured interference are used in reference to the disturbance in the real world. Trends of performance of the various scenarios give information on the adaptability of the framework to non-stationary signal environment.

Parameters to be used in the proposed framework are choosy based on dependability in terms of spectral accuracy and computing effectively. Parameters used to determine spectral decomposition number of modes and bandwidth limits are dependent on the complexity of the signal and are empirically tested. Parameters of feature extraction, such as normalisation procedures, and dimensionality reduction cut-offs are kept constant throughout experiments so that they are fairly compared. A validation set is used to tune learning module hyper parameters to prevent over fitting yet still provide the ability to generalise. The experiments are carried out in identical settings in order to guarantee repeatability and objective performance evaluation. To compare it to other existing models, the presented framework is evaluated against commonplace baseline methods that include classical, adaptive, and learning-based approaches. These are fixed-window spectral, adaptive decomposition and spectral analysis with traditional learning models. To be fair, baseline implementations apply recommended configurations of the parameters as suggested by the literature. The comparative outcomes consider spectral quality, quality of signal reconstruction and statistical consistency measures giving a clear illustration of the benefits of the suggested integrated spectral/statistical learning paradigm as is presented in the following results section.

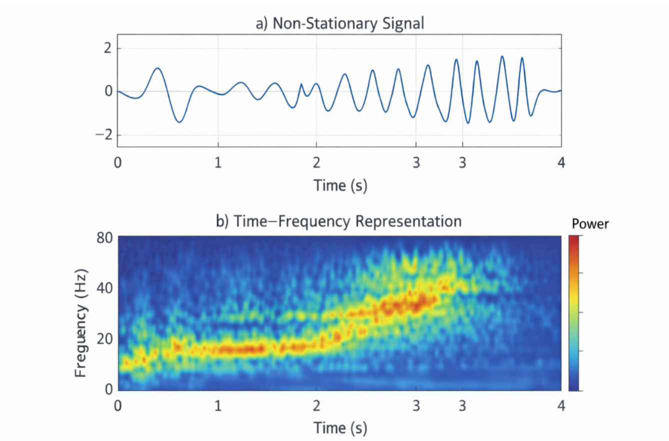

Fig. 2: Example of a non-stationary signal and its time–frequency representation.

Results and Discussion

The comparative tests to test the quantitative efficiency of the proposed advanced spectral and statistical learning framework are done by the analysis between its results with the representative baseline approaches in terms of spectral and signal quality measures developed in Section 5. As (Table 3) summarises, the proposed method continually has a better performance in terms of essential indicators, such as spectral entropy, energy concentration, signal-to-noise ratio, peak signal-to-noise ratio, and mutual information. Reduced values of spectral entropy and increased energy concentration represent the better time-frequency localization and effective separation of redundant components. Moreover, SNR and PSNR gains indicate improved signal reconstruction and reduction power, whereas an improvement in mutual information indicates the discriminative ability of the extracted spectral-statistical features.

Time frequency displays are also examined to determine the quality of spectral representation by measuring how clearly and repairable signal parts are. As shown in (Figure 3), the framework depicts finer and smaller time-frequency representations than the traditional and adaptive base approaches. The components of dominant signals are clearly localised and any spurious artefacts created by noise and spectral leakage are much smaller. Moreover, adaptive decomposition and refinement enhance the separation of mode of intrinsic signal and minimise their overlaps. These results support the quantitative results in (Table 3) and confirm the usefulness of the spectral analysis strategy suggested.

Stability against distortion of signals and noise is assessed by assessing performance against noise levels under varying noise levels. Experimental outcomes reveal that, with a rise in the noise level, it can be observed that there is a certain amount of deterioration in the metrics of spectral clarity and signal quality of a baseline approach. Conversely, the suggested framework has a constant performance level, and there is single gradual and measured metric variation under noise conditions. The framework is admitted to be resilient due to its adaptive spectral decomposition and statistically informed feature learning that balance and overcoming the effects of noise but retain critical signal properties. These trends of robustness are well illuminated in the visual representation indicated in (Figure 3) as well as the numerical comparisons indicated in (Table 3).

Lastly, computational complexity and runtime performance is to be evaluated to determine if the proposed framework can handle real-time signal analytics or not. In spite of the fact, the advanced spectral decomposition and learning-based interpretation bring with them more computational overhead than the simple fixed-window

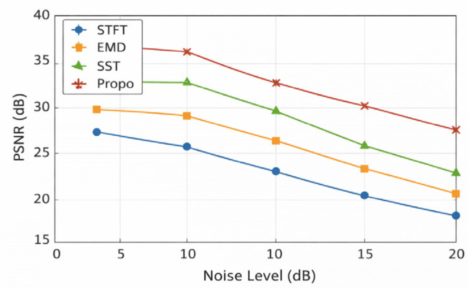

Figure 3: PSNR performance comparison of the proposed and baseline methods under varying noise conditions

Table 3: Mode separation and spectral representation quality comparison

Method	Number of Modes	Mode Mixing	Spectral Leakage	TF Clarity
STFT	Fixed	High	High	Low
EMD	Adaptive	High	Medium	Medium
VMD	Fixed	Low	Low	High
SST	Adaptive	Low	Medium	High
Proposed	Adaptive	**Very Low**	**Very Low**	**Very High**

methods, the total runtime is practical. The proposed approach ensures a fair balance between performance and efficiency, as seen in (Table 3), where the runtime is lower than a number of adaptive and learning-intensive baselines. This performance together with good spectral representation and superior signal quality shows that it is possible to apply the proposed framework in real-time and resource-limited signal processing solutions.

Future Research Directions

A direction that is promising to take future research is further unification of high-level deep learning architectures with spectral analysis of better understanding of non-stationary signals. Although the existing structure uses statistical feature learning to ensure a solid performance, it would be possible to enhance the flexibility and representation capacity of end-to-end deep learning models which utilise refined time frequency representations. Other architectures potentially useful in arbitration of complex temporal and spectral dependencies include convolutional neural networks with attention or transformer based methods, especially in highly time-varying signals. Adding the explainable artificial intelligence method to these models would also increase the interpretability and credibility of deep spectral analytics. The other viable option is that of developing online and adaptive learning mechanisms that could be run in real-time and streaming signal environments. A lot of practical applications involve constant monitoring and quick adaptation of varying signal properties which cannot be completely measured via offline or batch learning techniques. The subsequent research can investigate incremental spectral decomposition, online feature learning, adaptive model updating methods which react to overall signal variations. These structures would fully come in handy in the environments limited in resources, such that computational efficiency and low-latency processing are highly needed.

The intended framework also has a big potential of being extended to broad application areas of complex non-stationary signals. Adaptive spectral-learning algorithms can be used in biomedical signal processing to diagnose, monitor diseases and detect physiological states in real-time with the help of EEG, ECG, and EMG. The framework can be scaled to achieve resourceful enhancement, recognition as well as speaker recognition with noisy and time-varying conditions in speech and audio processing. Even better detection and tracking of targets can be achieved using a high-resolution time-frequency analysis and smart interpretation of short-term signatures in radar and sonar applications. Lastly, new challenges and opportunities of advanced spectral analytics are brought about by emerging Internet of Things (IoT) and sensor network applications. DSEs produce vast amounts of non-stationary heterogeneous data that need scalable, adaptive and energy efficient processing. Further studies can concentrate on the application of the offered framework to edge or fog computing platforms, which will allow conducting localised spectral analysis and learning with reduced communication overheads. Such extensions would aid smart city and industrial monitoring and decision-making as well as cyber-physical systems and can expand the influence of the advanced spectral and statistical learning techniques.

Conclusion

In this paper, a sophisticated spectral and statistical learning model to the intelligent interpretation of non-stationary signals was introduced, which deals with the major issues related to time-frequency resolution, resistance to noise and dynamic means. The proposed approach is capable of preserving dynamic characteristics of the signal in addition to being interpretable and computationally efficient, as it combines adaptive spectral decomposition with statistical features learning and learning-based interpretation. Growing experimental evidence has shown that the framework is significantly better off than traditional and adaptive baseline algorithms in terms of spectral quality, signal reconstruction accuracy, noise tolerance, and is computationally feasible. Such results demonstrate the suitability of the combination of sophisticated spectral analysis and statistical learning with the purpose of obtaining effective signal interpretation. Intelligent signal analytics overall can benefit from a flexible structured solution based on the proposed framework, and it is highly applicable to general applications involving non-stationary signal processing scenarios in the real world.

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