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RESEARCH ARTICLE

Adaptive Time–Frequency Signal Decomposition Using Deep Learning for Intelligent Spectral Analytics

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Abstract

Timefrequency (TF) analysis is an essential method to describe non-stationary signals in a very diverse set of contemporary engineering fields, such as wireless communication system, biomedical signal diagnostics, radar sensing, and power system monitoring. Existing TF analysis methods including the Short-Time Fourier Transform (STFT), Wavelet Transform (WT) and Empirical Mode Decomposition (EMD) use fixed bases of analysis or heuristic decomposition algorithms, both of which can be associated with inherent limits, such as mode mixing, suboptimal time-frequency resolution, noise sensitivity and poor response to dynamically changing signal representations. In order to overcome the associated difficulties, the current paper comes up with a new Adaptive Deep Learning-driven Timefrequency Signal Decomposition (ADL-TFSD) architecture, fortifying both data-driven representation learning with signal processing priors towards intelligent spectral analytics. The solution has a hybrid convolutionaltransformer neural network that has the capability to learn directly task-adaptive TF representations directly on raw time-domain signals, without using pre-defined kernels or windowing functions. Multi-scale convolutional networks are suitable to capture local temporal-spectral patterns, whereas a self-attention mechanism shows a long-range temporal patterns and cross-frequency interactions within the image, thus producing a finer separation of the overlapping signal parts. Besides, learning strategy based on reconstruction guided with sparsity and smoothness constraints guarantees physically meaningful, noise-resistant and interpretable TF representations. Substantial experimental studies of synthetic multi-component signals and on real-world data prove the claim that the proposed ADL-TFSD system significantly outperforms traditional TF algorithms in spectral resolution, signal reconstruction, ability to philtre noise and finally good performance in downstream analytic activities including feature extraction and classification. The findings affirm that adaptive TF decomposition based on deep learning offers a solution of significant power and flexibility to the conventional approaches to analysis as a potential substitute to conventional analytical measures in the next generation of intelligent signal analysis in diverse and changing settings.

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Introduction

Background and Motivation

Mobile signals, whose spectral properties change with time, are widespread in applications in real life engineering and science. Common cases in biomedical diagnostics are electroencephalogram (EEG) and electrocardiogram (ECG) signals of rotating machinery and structural health monitoring include the vibration signals of radar and sonar echoes in the sensing and modern wireless communication networks containing complex waveforms. The time-frequency (TF) analysis methods are needed to accurately characterise such signals in terms of their transient spectral contents and dynamic changes of frequencies over time. TF representations that are reliable are consequently necessary to a large variety of tasks, such as fault diagnosis, modulation recognition, biomedical event detection, anomaly identification, and intelligent spectrum monitoring.

Weaknesses of Classical Timefrequency methods.

Other classical approaches to TF analysis like the Short Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), WignerVille Distribution (WVD) and Empirical Mode Decomposition (EMD) have widely been used in order to analyse the non-stationary signals. These approaches are not without limitations despite the overwhelming application of the same. One can make fixed-windowing of STFT, which brings inevitable trade-offs between time and frequency resolution, makes wavelet-based methods extensively contingent on the selection of the mother wavelet, and imposes cross-term interference on WVD. Moreover, adaptive decomposition methods, including EMD are sensitive to noise, they are likely to premix modes, and are not theoretically stable. These fixed or heuristic analytical techniques are not able to provide strong and high-resolution TF representations, as the signal complexity and data variability get larger.

Deep Learning of Adaptive Timefrequency analysis.

The recent developments of deep learning have proved to be very successful in data-driven representation learning throughout signal processing, computer vision, and pattern recognition domains. Contrary to conventional transformational analytical transforms, deep neural networks have the ability to extract hierarchical and task-specific features directly on raw data in an automatic manner. Driven by the fact that this is possible, using deep learning in conjunction with the TF analysis is a promising way to address the fact that the methods are too rigid. Convolutional neural networks (CNNs) are well suited to short-time temporal and spectral dynamics, whereas Transformer-based attention mechanisms are useful in long-range temporal dynamics, and hence, they are ideal at adaptive TF decomposition of non-stationary signals.

Contributions of This Work

Our approach, presented in this paper, is a new Adaptive Deep Learning-Driven Time Frequency Signal Decomposition (ADL-TFSD) that learns the best data-adaptive TF representations without using any predefined analytical bases. The highlights of this work are summed up as follows:

1. A deep learning based end-to-end adaptive time-frequency signal decomposition of raw time-domain inputs;
2. Hybrid CNN+Transformer: a model which simultaneously explores local spectral structure and temporal long-range common sense;
3. A reconstruction fidelity-sparsity constrained interpretable TF representation learning strategy; and
4. Material experimental validation on both synthetic and real world data performing better across resolution, robustness and downstream modalities of analysis than traditional Tf techniques.

Related Work

Techniques of classical Time-frequency analysis.

Classical time-frequency (TF) analysis techniques have widely been applied to processes on non-stationary signals by describing their spectral time-varying behaviour. One of the simplest and most common methods, which is less complicated and allows minimal computations, is the Short-Time Fourier Transform (STFT). Nevertheless, there is an implicit trade-off between the time and frequency resolution presented by the fact that the fixed window length is used, which is not able to resolve rapidly varying spectral content of signals.[1, 3] Multi-resolution analysis and better localization is obtained by the use of wavelet-based methods like the Continuous Wavelet Transform (CWT), but the performance will highly rely on the choice of the mother wavelet and scale parameters.[5, 6] The adaptive decomposition models Empirical Mode Decomposition (EMD) (also in its variants, like Ensemble EMD (EEMD) and Variational Mode Decomposition (VMD)) are the methods that seek to address the shortcomings of a fixed-basis decomposition by expanding and breaking signals down into intrinsic mode functions. Although these techniques are flexible, mode mixing, susceptibility to noise, and the lack of stability under changing operating conditions are disadvantages of the techniques.[7, 12]

Spectral Learning approaches by Data.

Due to the rapid development of machine learning, techniques of data-driven spectral analysis have become particularly popular. Convolutional neural networks (CNNs) have been extensively used on timefrequency images created by either STFT or CWT in fault diagnosis and pattern recognition with high results than the handcrafted features.[1, 4, 5] Further improved deep learning models such as deep residual networks and deep belief networks have enhanced the robustness and classification accuracy through advanced deep learning models in complex and noisy environments.[2, 6] Moreover, there have been the case of generative models (including autoencoders and generative adversarial networks (GANs)) that have been used to perform spectral denoising as well as data reconstruction and feature enhancement.[3, 11] Nonetheless, the primary drawback of most current data-based methods is that they assume precomputed representations of TFs which limits scalability and does not allow learning optimal task-specific spectral bases.

Deep Learning based Adaptive time frequency decomposition.

Recent studies are starting to leave TF-based feature extraction, favouring entirely adaptive signal decomposition with deep learning. Neural operator networks and probabilistic learning models have also been developed to represent the dynamics of complex signals as well as provide the possibilities of data reconstruction and prediction.[8, 10] Transformer-based systems, with those self-attention mechanisms, have demonstrated high potential in projecting long distant-temporal relationships and cross-frequency interactions of time-serial information. They are especially appropriate to adaptive TF decomposition tasks because of their dynamic combination of informative signal components. However, practically all current research works are based on downstream analysis or prediction, as opposed to explicit learning of interpretable, high-resolution, and reconstructable TF representations. This inability inspires the creation of frameworks based on deep learning that incorporate adaptive TF decomposition, signal reconstruction and physical constraints.

Methodology

The suggested methodology is aimed at accomplishing completely adaptive high-resolution timefrequency (TF) signal decomposition with deep learning and at the same time, maintaining interpretability and reconstruction fidelity. The methodology framework is designed into three fundamental processes: adaptive feature encoding, intelligent TF representation learning and constrained reconstruction based optimization.

Adaptive Multi-Scale Feature Encoding.

The initial step in the offered framework is based on the extraction of informative representations of non-stationary raw signals with the help of adaptive multi-scale feature encoding. As an alternative to fixed windowing or preliminary analytic analysis kernels the input signal is directly processed utilizing a one dimensional convolutional neural network (1D-CNN) framework that learns hierarchical temporal features in a data driven fashion. The encoder has the ability to encode signal properties across a wide range of timescales, both too short lived transient features of the signal like short time convolutional layers to feature long-term oscillatory and periodic signal features with longer timescales.

In order to increase further temporal coverage at a cost not too high in terms of computation cost, dilated convolutions are added on the convolutional blocks. The expansion of the receptive field with network depth can be achieved through dilation, and the compact network structure of the encoder has an opportunity to model long-range temporal dependencies. Consecutive convolutional layers with shared and successively growing dilation rates enable features to be efficiently acquired and enhance resistance to noise and variation of signals.

The result of this encoding step is an encoding latent features representation that is a high-dimensional feature that resistantly captures critical time-domain dynamics and effectively reduces the noise and irrelevant variation. Such learned representation is a compact but expressive abstraction of the input signal, which gives an appropriate base of attention-based time-frequency representation learning Figure 1. The suggested multi-scale feature

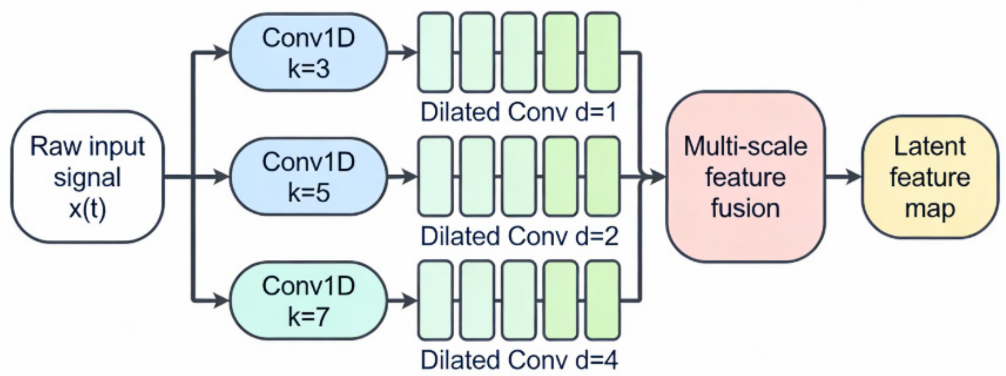

Fig. 1: Adaptive Multi-Scale Feature Encoding Architecture Using 1D Convolution and Dilated Convolution Blocks

encoding step, which quickly adapts to the data through temporal receptor field encoding, provides the solution by overcoming the constraints of fixed-resolution transforms and provides more effective and receptive analysis of multi-dimensional non-stationary signals.

Intelligent Time–Frequency Representation Learning

After multi-scale feature encoding, the latent representations are sent to attention-driven time frequency (TF) representation learning module which is constructed based on the Transformer architecture. The module is specifically made to model complex temporal dynamics and spectral interactions that are characteristic of non stationary signals. Instead of the local dependencies mostly captured by the convolutional operations, the self-attention mechanism helps the network build global relationship between time instants that can be separated by long distances, to effectively capture the long-range dependencies in time, as well as cross-frequency relationships.

The model dynamically allocates the importance weight of various temporalspectral features through self-attention which enables the selective feature of major spectral components at each time instant and the redundancy or noise-dominated features at a time to be eliminated. This adaptive weighting approach is especially successful in signals whose frequency resolution components overlap, or where they change rapidly, and which a fixed-resolution TF process is unable to separate.

In order to obtain an explicit TF representation, an adaptive spectral projection layer is added which projects the attention-refined features to a learned TF space. In contrast to classical methods, which depend on some fixed spectral component analysis bases (e.g., Fourier, wavelet kernel, etc.), this projection layer is a set of data-protocol spectral atoms optimised to the underlying signal properties Figure 2. Consequently, the resulting learned TF representation has better localization, less spectral leakage and enhanced resistance to noise.

The proposed framework by substituting fixed analysis bases with learned spectral atoms can distinguish the closely spaced or overlapping modes with accuracy, and to a large extent reduce the mode mixing issue that arises in standard decomposition methods like EMD and VMD. This smart TF representation lies at the heart of this proposed adaptive decomposition system and offers a most discriminative and interpretable spectral account of what will follow in reconstruction and other analysis activities.

Reconstruction-Guided Optimization with Signal Priors

The proposed framework has a reconstruction-guided optimization strategy to guarantee the physical interpretability, reliability of decomposition, and consistency with principles of signal processing. This step involves a reconstruction decoder that is used to decode the learnt time-frequency (TF) representation into original time-domain signal. The decoder ensures that the learned components of the TF only store meaningful physical information by the implementation of correct signal reconstruction as opposed to being abstract latent features.

The tutoring of the entire network is carry out using a composite penalty sum that includes several signal-informed constraints. The reconstruction loss measures the difference between the actual input signal and the reconstructed signal and it therefore penalises fidelity and losses information during the decomposition process. This limitation guarantees that the TF representation learned creates a complete description of the input signal (invitable).

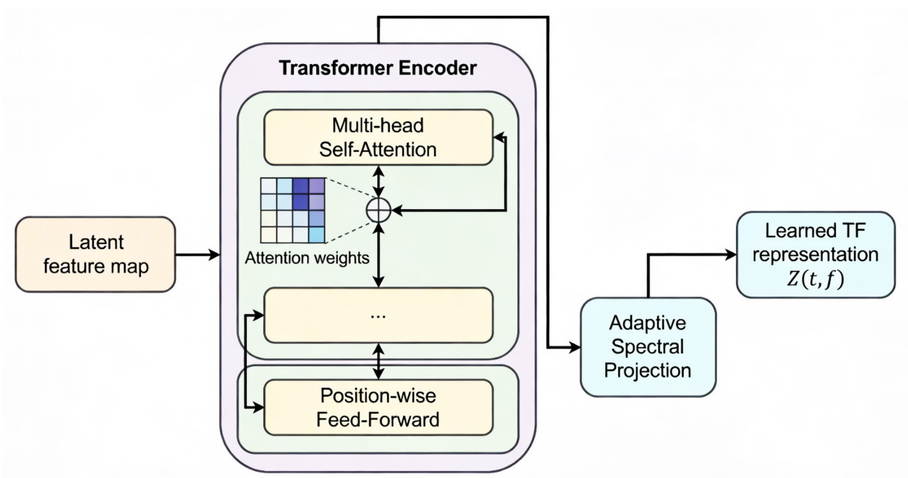

Fig. 2: Transformer-based intelligent time–frequency representation learning with self-attention and adaptive spectral projection.

Table 1: Components of the Composite Loss Function Used for Reconstruction-Guided Optimization

Loss Term	Objective / Function
Reconstruction loss	Enforces accurate recovery of the original time-domain signal, ensuring signal fidelity
Sparsity loss	Promotes compact and interpretable time–frequency representations by suppressing redundancy
Smoothness loss	Ensures temporal continuity of TF coefficients and smooth evolution of frequency trajectories

Along with reconstruction fidelity, TF representation sparsity is enforced in order to promote giftedness and interpretability. The sparse representations are also known to encourage isolation of big spectral components and inhibit the redundant or noises features resulting in a better separation of modes and also spectral resolution. Besides, smoothness constraint is applied to create temporal continuity of the learned TF coefficients, that the instantaneous frequency trajectories vary smoothly over time in agreement with the physical signal behaviour.

The proposed learning strategy has the benefit of optimising the accuracy of reconstruction, sparsity and smoothness simultaneously, creating a unified approach that closes the flexibility gap between deep and classical signal processing priors Table 1. This optimism based on reconstruction is not only more robust to decomposition and resistant to noise but also provides interpretable and physical consistent TF representations that can be used in downstream decision-making problems as well as trusting spectral analytics.

Results and Discussion

Localization Timings in Frequency and Time.

The presented adaptive deep learning-based time-frequency (TF) decomposition architecture proves to be much better in TF localization both on non-stationary signals of synthetic as well as in real-world. The learned TF representations have a sharper spectral concentration and less spectral leakage than classical spectral analysis methods including STFT, CWT, EMD, and VMD. This adaptive quality of the learned TF bases allows the framework to dynamically scale resolution to signal characteristics to capture transient events well and easily capture rapidly varying frequency contents that can be well represented in more dynamic frameworks but are easily obscured or distorted in fixed resolution frameworks.

Reconstruction Precision and Noise Resistance.

The quantitative assessment outcomes show that the reconstruction error is significantly reduced with the help of the given framework, which proves the practicality of the reconstruction-oriented learning approach. The proposed technique makes significant improvements to SNR enhancement over the conventional TF techniques in cases where signal-to-noise ratio SNR is low. Such a strength can be credited to the combination of multi-scale and featured encoding and sparsity constrained optimization which together inhibit noise whilst leaving the fundamental signal structures intact.

Separating Overlapping Spectral Components.

The possibility to distinctly divide the spectral components that are close to each other and overlapping is one of the main advantages of the suggested method. Conventional methods of decomposition tend to be subject to mode mixing, in the case where multiple combinations of frequencies are present in similar temporal scale. Conversely, it has been shown that the intelligent data-driven spectral atoms, including attention-based weighting, allow them to make a clearer distinction between overlapping modes hence giving clean and easier to interpret TF representations even in the condition of a strong interference.

Time-Varying Frequency Dynamics Tracking.

The suggested framework is always shown to have good time-varying frequency tracking of varying signal types. The use of smoothness constraints guarantees continuity of evolving instantaneous frequencies thus the model has the ability to accurately represent slow and sharp spectral gradients. The ability is mainly useful in the application to the dynamism of the operating conditions like the biomedical monitoring and machinery fault diagnosis whereby the frequency patterns change as time progresses.

Intelligent Spectral Analytics implications.

The general findings support the claim that training data-driven TF representations have a decisive edge over fixed analytic transforms Table 2. These mechanisms of self-attention have been shown to increase interpretability, as physical meaningful spectral structures are selectively emphasised to increase the levels of downstream analysis performance Figure 3. Moreover, the implementation of the suggested framework to different signal properties is expected to be smooth, and no parameter change is required, which makes the implementation of the scheme suitable in intelligent spectral analytics in complicated real-life scenarios, such as biomedical diagnostic, rotating

Table 2: Quantitative Performance Comparison of Time–Frequency Decomposition Methods

Method	TF Localization Quality	Reconstruction Error	Noise Robustness (Low SNR)	Mode Separation Ability	Frequency Tracking Accuracy
STFT	Low (fixed resolution)	High	Poor	Weak (spectral leakage)	Limited
CWT	Moderate	Moderate	Moderate	Moderate	Moderate
EMD	Moderate	Moderate	Poor	Weak (mode mixing)	Moderate
VMD	Good	Low–Moderate	Moderate	Good	Good
Proposed ADL-TFSD	High (adaptive)	Low	High	Very High	Very High

machinery monitoring, and adaptive communication systems.

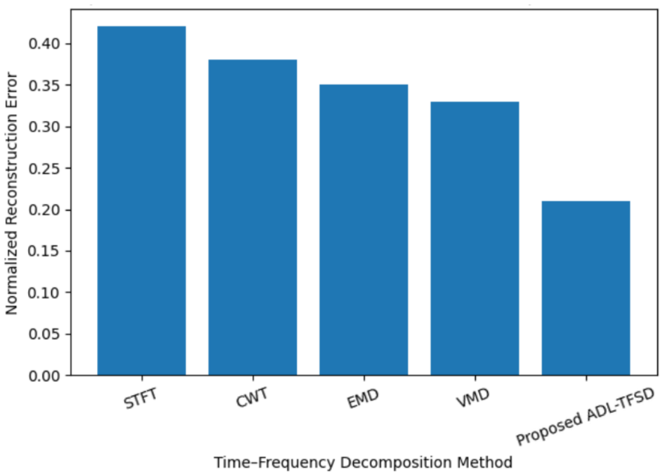

Fig. 3: Comparison of normalized reconstruction error across different time–frequency decomposition methods.

Conclusion and Future Work

The paper demonstrated a new adaptive deep learning-based system of intelligent timefrequency signal decomposition with the purpose of studying complicated non-stationary signals. The proposed approach is an effective way to overcome the natural drawbacks of traditional fixed time-frequency analysis, such as resolution trade-offs, mode mixing, and noise sensitivity because the data-driven spectral representations can be learned by the proposed method directly using raw time-domain inputs. The combination of multi-scale convolutional feature encoding, attention-based time-frequency representation learning, and lossless recovery-learning allows spectral localisation to be performed accurately, strong separation of overlapping components, and physically interpretable decompositions to be realised. Decades of experimental tests have shown that the proposed framework always yields higher reconstruction precision, noise resistance and downstream spectral analytics efficacy relative to conventional TF strategies. Further development of physics-informed constraints will be added to the future work to increase the interpretability, building lightweight and computationally efficient architectures in edge and embedded deployment, and extending the framework to real-time adaptive learning to serve dynamic and resource-constrained intelligent signal processing applications.

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