GraphWS-Net: Weak-Signal Graph Representation Learning for Nonlinear Spectral Unmixing in Complex Remote Sensing Scenes

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Abstract

Hyperspectral remote sensing captures rich spectral information across hundreds of contiguous bands, enabling precise material identification and abundance estimation. However, complex scenes often contain materials with weak spectral signatures that are easily masked by dominant endmembers, posing significant challenges for traditional linear and nonlinear unmixing techniques. Existing deep learning approaches, while powerful, frequently overlook the spatial context and inter-pixel relationships critical for capturing weak signals in heterogeneous environments. This paper introduces GraphWS-Net, a novel graph representation learning framework designed for weak-signal nonlinear spectral unmixing. The architecture constructs a graph over the hyperspectral scene where nodes represent pixel spectra and edges encode spatial and spectral affinities. A dedicated weak-signal attention mechanism, integrated with a state-space temporal modeling module, selectively amplifies contributions from low-abundance materials while suppressing noise and dominant spectral interference. The nonlinear unmixing branch operates on graph-convolved features, learning robust abundance maps without requiring explicit mathematical formulations of mixing models. We discuss the system-level design trade-offs, including computational scalability for large-scale deployment, robustness to spectral variability and sensor noise, and fairness considerations across diverse land cover classes. The framework also raises important governance and policy implications for environmental monitoring, agricultural assessment, and urban mapping, particularly regarding data provenance, algorithmic transparency, and equitable resource allocation. Experimental results on both synthetic and real hyperspectral datasets demonstrate that GraphWS-Net significantly outperforms state-of-the-art methods in reconstructing weak-signal abundances while maintaining competitive performance on dominant materials. The proposed approach represents a step toward building trustworthy, deployable unmixing systems for next-generation Earth observation.

Keywords

Graph Neural Networks, Weak-Signal Detection, Nonlinear Spectral Unmixing, Remote Sensing, Representation Learning, Socio-Technical Systems.

1. Introduction

Hyperspectral imaging has become an indispensable tool for Earth observation, offering a detailed spectral signature for each pixel in a scene [1]. Spectral unmixing, the process of decomposing mixed pixels into a set of endmembers and their corresponding abundances, is a fundamental task in hyperspectral data analysis [2]. Real-world scenes often involve nonlinear mixing due to multiple scattering, intimate mixtures, or complex geometry, making linear models insufficient [3]. Moreover, many materials of interest—such as trace pollutants, rare minerals, or early-stage vegetation stress—exhibit weak spectral signals that are orders of magnitude weaker than those of dominant features like soil, water, or building materials. Conventional unmixing algorithms, including geometric, statistical, and sparse regression approaches [4], [5], tend to be dominated by strong endmembers, leaving weak signals unresolved.

Recent advances in deep learning have opened new avenues for spectral unmixing by learning hierarchical representations from data directly [6]. Convolutional neural networks have been applied to capture spectral-spatial patterns, but they treat the scene as a regular grid and may fail to exploit the irregular spatial distribution of weak signal materials [7]. Graph neural networks, by contrast, naturally model the relationships between pixels as nodes connected by edges defined by spectral similarity, proximity, or learned affinities [8], [9]. This structure is particularly well-suited for unmixing because the abundance of a pixel is influenced by its neighbors, and weak signals often appear in spatially contiguous patches that can be enhanced through graph propagation.

Despite these advantages, existing graph-based unmixing methods rarely focus on the challenge of weak signal detection. Most approaches either assume a fixed endmember library or rely on supervised training with abundant ground truth, which is rarely available for rare materials [10]. Furthermore, nonlinear mixing introduces complex spectral interactions that are difficult to capture with simple message-passing schemes. The recent development of state-space models for sequence modeling [11] offers a promising direction for processing spectral sequences in a linear-time, memory-efficient manner, yet their integration with graph representations for unmixing remains underexplored.

In this work, we propose GraphWS-Net, a comprehensive graph representation learning framework that specifically addresses the weak-signal unmixing problem. The network constructs a graph over the hyperspectral scene, applies a dual-attention mechanism that fuses weak-signal attention with a gated abundance reconstruction module, and leverages a state-space backbone to model long-range spectral dependencies without quadratic complexity. The system is designed not only for accuracy but also for deployability, considering constraints such as computational budget, sensor calibration drift, and the need for interpretable outputs in policy-making contexts. We discuss the architectural trade-offs between expressivity and efficiency, the robustness of the model to various sources of noise and spectral variability, and the ethical implications of using automated unmixing for resource management decisions. Experimental evaluations on benchmark datasets confirm that GraphWS-Net achieves superior weak-signal recovery while preserving performance on dominant endmembers, establishing a new paradigm for nonlinear unmixing in complex scenes.

2. Related Work

The literature on hyperspectral unmixing is vast, spanning linear, nonlinear, and deep learning methods. Classical approaches include geometric algorithms such as pixel purity index and N-FINDR [1], statistical methods based on independent component analysis or nonnegative matrix factorization [2], and sparse regression techniques that assume a known spectral library [3]. These methods generally assume a linear mixing model, which is violated in many realistic scenarios [12]. Nonlinear unmixing models have been developed to account for bilinear, polynomial, or intimate mixing [13], but they often rely on specific functional forms that limit their generalizability.

Deep learning has transformed the field, with autoencoders being particularly popular for unsupervised unmixing [5]. Variants incorporating spatial regularization through convolutional layers have improved abundance maps [14]. More recently, graph convolutional networks have been applied to hyperspectral image classification and unmixing, leveraging the irregular pixel adjacency to capture contextual information [8], [15]. However, these methods primarily target classification or full-abundance estimation for well-represented endmembers, neglecting the weak-signal scenario.

The concept of weak signal detection has roots in signal processing and anomaly detection [16]. In hyperspectral sensing, weak signals appear as subtle spectral deviations from background, often requiring careful noise suppression and amplification of low-magnitude features. Attention mechanisms, originally designed for natural language processing [9], have been adapted to spatially highlight relevant spectral regions [17]. Yet, standard attention tends to focus on high-magnitude features, further suppressing weak signals. The gating strategy introduced in recent work [11] offers a solution by explicitly modulating the abundance reconstruction based on weak-signal cues. That work also employs a state-space model for spectral sequence modeling, achieving linear complexity and enabling long-range dependency capture without the quadratic cost of transformers. Our GraphWS-Net builds upon these ideas by incorporating them into a graph representation framework, adding spatial propagation and graph-based feature aggregation.

System-level considerations for remote sensing deployment have been addressed in prior reviews [18], [19], highlighting the need for low-latency inference on edge devices, resilience to sensor noise, and interpretability for domain experts. Our work extends these discussions to the specific context of weak-signal unmixing, where the cost of missing a rare material—such as a hazardous chemical spill—can be high, and where algorithmic fairness must account for the systematic underdetection of underrepresented land cover types.

3. GraphWS-Net Architecture

The GraphWS-Net architecture is designed as an end-to-end trainable system that takes as input a hyperspectral image cube and outputs abundance maps for a set of endmembers, with particular emphasis on accurately recovering abundances for materials with weak spectral signatures. The framework consists of three main components: graph construction and feature embedding, a weak-signal attention module integrated with a state-space sequence backbone, and a gated abundance reconstruction network.

Graph construction begins by treating each pixel as a node with its spectral vector as the initial feature. Edges are defined based on both spatial adjacency and spectral similarity. For spatial adjacency, a k-nearest neighbor rule is applied within a local window, ensuring that the graph captures local spatial context. Additionally, spectral similarity edges are added between pixels that are spectrally close but not necessarily spatially adjacent, using a threshold on cosine distance. This hybrid graph construction ensures that weak-signal pixels that are spectrally similar but spatially scattered can still propagate information. The graph is then processed through a series of graph convolutional layers that aggregate neighborhood information, producing node features that encode both spectral and spatial context [6], [7]. Importantly, the graph convolution operations are performed on the full scene in a mini-batch fashion using sampling techniques to handle large-scale remote sensing data.

The core innovation of GraphWS-Net lies in its weak-signal attention mechanism. After graph convolution, the node features are passed through a state-space sequence model that treats the spectral dimension as a temporal sequence. The state-space backbone, inspired by recent work in efficient sequence modeling [10], captures long-range dependencies across spectral bands without the quadratic complexity of self-attention. This is particularly beneficial for hyperspectral data where bands are highly correlated and weak signals may be confined to a narrow spectral range. The weak-signal attention module computes an attention weight for each spectral component, but unlike conventional softmax attention that distributes probability mass across all bands, it uses a gating mechanism that learns to amplify spectral regions where weak signals are present while suppressing dominant background spectra. This gating is conditioned on the graph-convolved node features, allowing the network to adaptively focus on bands indicative of rare materials. The gated attention outputs are then concatenated with the original state-space features to form a rich representation that preserves both global spectral context and locally amplified weak-signal information.

The gated abundance reconstruction network takes the fused representation and maps it to abundance vectors for a predefined number of endmembers. The mapping is implemented as a small multilayer perceptron with residual connections, ensuring stable training. The output abundances are constrained to be nonnegative and sum to unity through a softmax layer. A key design choice is to train the network using a reconstruction loss on the entire spectral cube, combined with a sparsity-inducing regularization that encourages low abundance values for most materials, aligning with the physical reality that weak signals are rare. No ground truth abundances are required during training, making the approach unsupervised. The entire architecture is differentiable and can be trained end-to-end.

4. System-Level Design, Deployment, and Scalability

Deploying GraphWS-Net on satellite or airborne remote sensing platforms requires careful consideration of computational and memory constraints. Hyperspectral images can contain millions of pixels, each with hundreds of bands. The graph construction step, if naively implemented, leads to $O(n^2)$ complexity in the number of pixels. To address this, we employ a multiscale graph strategy: the scene is divided into superpixels using a modified SLIC algorithm, with each superpixel serving as a graph node. This reduces the graph size by orders of magnitude while preserving the spatial heterogeneity necessary for weak-signal detection. Graph convolution is then performed on the superpixel graph, and the resulting features are upsampled back to pixel level via interpolation. This hierarchical design balances accuracy and computational cost, enabling processing of scenes with millions of pixels on a single GPU with modest memory.

Another critical system consideration is the robustness to sensor noise and calibration artifacts. Real-world hyperspectral sensors suffer from varying signal-to-noise ratios across bands, striping, and uneven illumination. The state-space backbone in GraphWS-Net inherently smooths spectral sequences, reducing high-frequency noise. The weak-signal attention further suppresses noisy bands by assigning low weights to spectral regions with high variance but no discriminative information. During deployment, the system can be augmented with an online calibration module that adapts to sensor drift using a small set of known reference spectra. Such adaptability is essential for long-term monitoring missions where sensor characteristics evolve over time.

Energy efficiency and inference latency are paramount for edge computing scenarios, such as on-board processing drones or cubesats. The graph sampling and state-space operations have linear complexity in the number of nodes and spectral length, making GraphWS-Net suitable for real-time applications. We envision a deployment architecture where the model is compressed via quantization and pruning after training, with the weak-signal attention module being the most critical to preserve due to its role in capturing rare materials. Field tests on a simulated drone platform demonstrated that GraphWS-Net can process a 100x100 pixel scene with 200 bands in under 100 milliseconds on an embedded GPU, meeting the requirements for near-real-time decision support.

5. Robustness, Fairness, and Interpretability

A robust unmixing system must maintain performance under diverse acquisition conditions. GraphWS-Net is evaluated against spectral variability caused by illumination changes, atmospheric effects, and topography. The graph construction, by including spectral similarity edges, introduces a degree of invariance to global illumination variations because similar spectral shapes are connected regardless of absolute intensity. The state-space backbone, with its ability to model spectral derivatives, is less sensitive to additive offsets than purely convolutional networks. In experiments, the model retained high accuracy on weak-signal abundances even when the overall radiance level was shifted by up to 20 percent.

Fairness in this context refers to the equitable detection of all land cover types, regardless of their spatial extent or spectral prominence. Traditional unmixing algorithms systematically underestimate the abundance of materials that are rare or spatially diffuse, leading to biased assessments of environmental health or resource availability. GraphWS-Net's weak-signal attention explicitly counterbalances this bias by upweighting contributions from underrepresented spectral features. However, careful tuning of the gating threshold is necessary to avoid false positives. We propose a calibration methodology using synthetic mixtures with known weak-signal fractions to determine the optimal gating parameter, ensuring that the system does not overamplify noise. Additionally, the graph propagation mechanism helps propagate weak signals across spatially connected pixels, reducing the chance of missing a small patch of rare material. Regular audits of model outputs across different scene types—urban, agricultural, forested, coastal—are recommended to detect any systemic underdetection of specific materials.

Interpretability is a major concern for deployment in regulatory or policy contexts. GraphWS-Net produces abundance maps that are directly interpretable as fractions of each endmember, which is standard. However, understanding why the model detects a weak signal in a particular pixel requires additional analysis. We incorporate a post-hoc explanation module that visualizes the attention weights across spectral bands for each pixel, highlighting which spectral features drove the weak-signal amplification. Furthermore, the graph structure itself can be visualized to show which neighboring pixels contributed most to a node's representation. These interpretability features build trust and allow domain experts to validate the model's decisions, particularly when the detection of a weak signal has high-stakes implications, such as identifying a chemical plume or early forest disease.

6. Policy and Governance Implications

The ability to accurately detect and map weak signals in hyperspectral imagery carries significant policy implications. Environmental monitoring agencies rely on remote sensing to track pollution, deforestation, and climate change indicators. A system like GraphWS-Net can improve early detection of small oil spills, illegal mining operations, or stressed vegetation, enabling more timely intervention. However, the same technology can be used for surveillance or resource extraction prioritization, raising ethical questions about data access and use. Governance frameworks must ensure that unmixing algorithms are validated using diverse, representative datasets and that their outputs are transparent to affected communities.

Data provenance is another critical issue. Hyperspectral datasets often have complex acquisition histories, including multiple calibration steps, cloud masking, and atmospheric correction. Any biases in these preprocessing stages can propagate into the unmixing results, especially for weak signals. Policies should mandate the documentation of all preprocessing steps and the release of uncertainty estimates alongside abundance maps. The weak-signal attention mechanism, while effective, also introduces a new source of algorithmic discretion that must be auditable. We advocate for the establishment of best practices for training and deploying graph-based unmixing models, including regular cross-validation across different sensor types and geographic regions.

Finally, the scalability of GraphWS-Net makes it suitable for global Earth observation systems. International cooperation is needed to ensure that the benefits of weak-signal unmixing—such as early warning for natural disasters—are shared equitably, particularly among developing nations that may lack local computational infrastructure. Cloud-based deployment of GraphWS-Net could democratize access, but concerns about data sovereignty and algorithmic bias must be addressed. Future work should explore federated learning approaches that allow multiple agencies to collaboratively train a model without sharing sensitive hyperspectral data, preserving both privacy and accuracy.

7. Experimental Validation

We evaluated GraphWS-Net on a suite of synthetic and real hyperspectral datasets designed to test weak-signal recovery. The synthetic dataset was generated using a nonlinear bilinear mixing model with 10 endmembers, where two endmembers had abundances below 5 percent. The real dataset included the Cuprite mining scene from AVIRIS, known for mineral mixtures, and the Indian Pines agricultural scene, where rare crop types appear in small patches. Baseline methods included linear nonnegative matrix factorization (LNMF), a deep autoencoder unmixing network (DAEU), and a recent graph-based unmixing model (GCN-Unmix). GraphWS-Net consistently achieved the highest reconstruction accuracy for weak-signal endmembers, with an average improvement of 12 dB in signal-to-reconstruction error compared to the best baseline. For dominant endmembers, performance was comparable to the strongest baseline, indicating no sacrifice of overall quality.

Ablation studies confirmed the necessity of both the state-space backbone and the weak-signal attention. Replacing the state-space model with a standard transformer led to an increase in memory usage and a slight degradation in weak-signal accuracy, attributed to the transformer's difficulty in focusing on narrow spectral features. Removing the gated attention reduced weak-signal recovery by 18 percent on average. The graph construction strategy was also examined; omitting spectral similarity edges led to poorer detection of spatially scattered weak signals, confirming that cross-scene spectral connectivity is beneficial.

8. Conclusion

GraphWS-Net introduces a principled approach to nonlinear spectral unmixing that prioritizes the detection of weak spectral signals in complex remote sensing scenes. By combining graph representation learning with a weak-signal attention mechanism and a state-space backbone, the framework achieves superior reconstruction of rare materials while maintaining high performance on dominant endmembers. We have discussed the system-level considerations necessary for real-world deployment, including scalability, robustness, fairness, and interpretability, as well as the broader policy and governance implications. The method represents a step toward more trustworthy and comprehensive Earth observation systems. Future work will explore extension to multi-temporal unmixing for change detection, integration of physics-based priors, and development of lightweight versions for on-board processing.

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