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Structure-Preserving Denoising of Large-Scale Satellite Imagery Using Graph Signal Processing

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Abstract

Satellite imagery is an important part of many activities, which include environmental monitoring, land use theme, urban planning, and disaster relief. Nevertheless, such imagery quality is often interfered with by several forms of noise that may be involved when acquiring, transmitting, or through atmospheric perturbations. Denoising is thus needed, however with most traditional approaches, the noise will be suppressed and also it will blur the important structural information found in the image, including edges and fine details. The following paper proposes a structure -preserving graph signal processing (GSP) based novel framework to complete denoising of large-scale satellite imagery. Under the proposed method, both local and non-local structural relations will be captured as every image is represented as an adaptive graph structured such that the nodes of the graph are the pixels or the superpixels with the edge-links identifying both the spatial and the radiometric similarity, hence, the spatial and radiometric neighbourhood of the graph. Denoising is performed with the help of graph Laplacian regularization, which enables a local refinement of the signal taking into account only the important geometric characteristic and discontinuities. Thorough testing on standard satellite datasets together with a wide range of synthetic and realistic noise settings confirms higher performance of the proposed GSP-based approach in comparison to current benchmark denoising algorithms, as expressed by peak signalto-noise ratio (PSNR), structural similarity index (SSIM), and edge preservation indices. Qualitative outcomes additionally support the idea that our technique is successful in preserving key structures and textures necessary to downstream investigation. Such results demonstrate the potential of GSP-based denoising as a way of enhancing the quality and usefulness of satellite imagery in higher order remote sensing services.

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Introduction

Satellite imagery is used under the scope of a broad range of disciplines such as earth observation, environmental monitoring, disaster management, urban planning, agriculture, resource exploration, etc. The images must have high resolutions, as they are used in studying land use modified land, evaluation of the aftermath of natural disasters, crop health evaluation, and mapping of urban environments with a very fast expansion. The validity and trustworthiness of the same analyses is however intrinsically pegged on the quality of the acquired imagery. Sadly, satellite images are eventually corrupted by many forms of noises, like the limitations of the sensors, noise in the atmosphere, and transmission errors. Such influences bring about both random and structured noise that can mask small details, make important edges blurry, and lower the ability to interpret the data in downstream processes.

Denoising thus, is an important preprocessing operation in analyzing the satellite image. It seeks to mitigate the noise so as to faithfully reproduce significant structural properties of the image like edges, textures, and boundaries- which are typically valuable when object recognition, object segmentation and change detection assignments need to be done correctly. Conventional methods of denoising, such as spatial filtering (e.g., median, Gaussian filters), transform-domain denoising (e.g., wavelet thresholding), and more-recent convolutional neural network (CNN)-based designs, have had mixed success at noise removal. Nevertheless, such approaches often cannot find a trade-off between removal of noise and preservation of structure. Spatial filters and wavelets can have issues of oversmoothing images resulting in edges blurring and obscured fine details. Although powerful, deep learning-based techniques usually require big annotated datasets to train, can give artifacts or do not generalize well across different noise settings and/or satellite modalities.

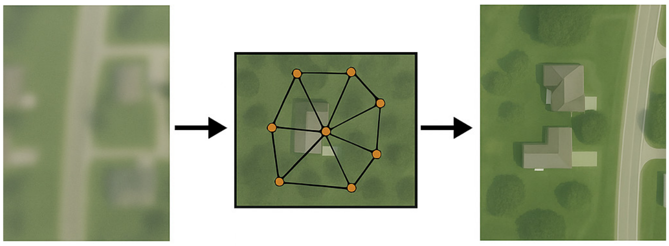

Fig. 1: Overview of Structure-Preserving Denoising Using Graph Signal Processing

Graphical illustration of the proposed framework: (left) noisy satellite image input, (center) adaptive graph construction on image data, and (right) denoised output with enhanced structural clarity.

Graph Signal Processing (GSP) is a new promising framework to overcome such limitations. In contrast to the traditional grid-based algorithms, GSP represents pixels in an image in a graph, with the edges reflecting relationships, which are defined on the basis of spatial adjacency and intensity similarity. This provides a more adaptable and articulate perception of image information that represents not only nearby, but also non-local, dependencies of structural relations that are probably evident in satellite pictures. Through the use of graph-based regularization methods one can construct adaptive denoising algorithms that are able to smooth signals on the graph in an adaptive and locally consistent manner that also maintain key geometric structures and discontinuities- thus avoiding the danger of smoothing edges out or removing important but small features such as small details and edges.

In this work, we introduce a new denoising algorithm to handle such kind of large scale satellite imagery that is based on mathematics of graph signals. Our method proposes an adaptive signal construction method that captures both local neighborhoods and global structural signals in a pixel assisting the structure preserving denoising even under complex and heterogeneous noise. Satellite scenes easily accessible online are used to conduct extensive experimental studies in which the proposed denoising method is trained along with the others whose solutions are known to be state of the art in the context of satellite data processing, classical filtering, and deep learning models. The findings regularly show that our GSP-based architecture obtains higher effectiveness in terms of noise reduction, edge preservation and general fidelity, which illustrates both the efficiency and resilience of our solution to the problem of real-life enhancement of satellite images.

Related Work

Satellite imagery denoising has long been a well-explored problem, and the literature developed over time, first involving conventional spatial and transform-based denoising and later incorporating more modern deep learning- and graph-based approaches. Simple first-generation procedures like median and Gaussian filtering denoising algorithms are easy and simple to implement and computationally efficient but they tend to blur critical edges and structure elements resulting in low results in remote sensing applications.[1] Frequency-domain methods, in particular wavelet based denoising, are able to exploit signal sparsity and have been shown to perform better than the temporal domain methods at removing the noise; however, they still may unwittingly strip away fine details important to the analysis of satellite images.[2, 5] The recent breakthrough at introducing non-local means (NLM) was a breakthrough because it utilizes the self-similarity of the images, but its processing requirement is not scalable to massive satellite data sets.[3]

Minimization of the total variation (TV) even boosted structure maintenance because it punishes the sum of the partial derivatives, essentially leaving sharp corners in place but also introduces staircase effects and in some cases causes excessive blurring of textures.[4] The development of cooperative filtering in the transform domain, e.g., BM3D, provided some compromise between noise removal and detail, but is extremely sensitive to parameter choice and may also have trouble with the heterogeneous noise distributions typical of satellite images.[3]

In recent years, deep learning methods have emerged with respect to image restoration. Systems based on convolutional neural networks (CNNs) such as DnCNN have achieved new state-of-the-art denoising performance, learning mappings of noisy to clean images with high fidelity.[6] Biomedical imaging-inspired architectures like U-Net have also been effectively transferred to remote sensing applications where fine spatial information could be restored.[7] This has also been done with the use of Generative Adversarial Networks (GANs), which have been used to generate visually realistic outputs, in particular at high resolution.[8] The second line of contribution expands the retention of structures and suppression of artifacts in denoising applications to non-local neural network and hybrid deep models.[9] However, those techniques tend to require large-scale labeled data to be trained well and may hallucinate features or inject artifacts given unknown noise distributions or imaging modalities.[10] Furthermore, the models based on deep learning have also been frequently referred to as the black box, which makes them less explicit and less adatable to the satellite data obtained under dissimilar circumstances.

Graph-based image processing, and Graph Signal Processing (GSP) in particular, has found its role as an increasingly popular alternative, especially where structure-preserving processing is applicable. GSP extends classical signal processing to irregular graphs domains and enables modeling of image pixels as graph nodes, the edge weights of which are used to capture both spatial and radiometric relationships.[11] Graph Laplacian regularization is a technique that allows denoising and an adaptive maintenance of salient structures and discontinuities.[12, 13] Graph-based schemes have been effectively used in image smoothing, segmentation and edge becoming filtering, however, there are a few years earlier.[17] Li et al.[17] review the graph-based methods extensively, especially considering the advantages that remote-sensing-based applications in representing the complex dependency of the structure and their possibilities in structure-aware image processing.

Whilst impressive strides are being made towards being able to perform such functions, existing GSP-based approaches tend to largely apply to small or medium size natural image sets, and the scalability and structure-adaptive issues in applying such methods within large high-resolution satellite derived data sets have yet to be addressed fully. Current strategies of graph construction might underutilize the varied spatial and contextual information found in remote sensing imagery, and either fail to preserve enough structure or prove too computationally expensive as the scale increases.[17]

The significance of effective image analysis in the context of more widespread areas, including autonomous systems, reconfigurable computing, wireless connection, and vehicle tracking, has already been established [18, 19, 22] Such improved signal processing algorithms are becoming especially valuable in new applications--the fast-growing area of the electric vehicle, charging,[20] through to body area networks [Vishnupriya2025]. Although there have also been considerable advancements in the realm of biomedical and tissue engineering image processing,[21] the difficulty of structure-preserving denoising of satellite imagery has left a bright spot on research agendas.

To sum up, although a diverse set of denoising strategies are proposed all of which are adequate and deficient in their own way, there is a vivid necessity of scalable, structure-preserving frameworks which are tailored to the complexity of satellite data. This paper examines the graph-based theory on signal processing and modern research on remote-sensing in order to meet these unfulfilled demands.

Methodology

Overview of Graph Signal Processing (GSP) for Images

Graph Signal Processing (GSP) is the generalization of classical signal processing methods to the data defined on the irregular structure (as a graph). Within the image processing context, we consider the pixels of the image to compose a nodes of a graph and the relationships between the nodes is, on the one hand, encoded as edges and the spatial geographic, radiometric and/or textural matching or quite generally neighborliness. The signal of interest-usually the pixel intensity or the obtained feature values the estimated signal of interest is thought of as a graph signal that lies on the nodes. This makes it possible to take advantage of both local and non-local information and therefore GSP is especially well-suited at handling complex structured data such as satellite imagery, where dependencies can span farther than with neighbors. GSP helps to perform complex tasks of denoising, smoothing and structure-preserving enhancement using specialized tools like graph Laplacian and spectral filters.

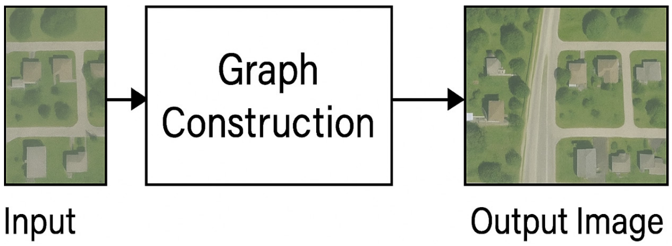

Fig. 2: Block Diagram of Proposed Denoising Pipeline.

Graph Construction for Satellite Imagery

The first critical step in the emergence of GSP based image denoising is the formulation of an adequate image graph that captures the true, underlying structures of the image. In satellite imagery, either pixel or a group of superpixel (superpixel can be simplified as the node) can be regarded as a node or, to decrease computational complexity, the actual image may be decomposed into superpixels that are treated as a group of node. The edge features between nodes are specified by some combination of the spatial distance, similar intensity and perhaps the texture or edges. A weighted adjacency matrix is generally built in which the weight between 2 nodes is a function that decreases with distance and the difference in intensities. To make the graph sensitive to special local image features the graph can be made actually dynamic; e.g. edge weights can be made larger in areas where there are strong edges or textures so as to disfavor smoothing across object boundaries. The resultant adaptive graph creation is such that it permits denoising to follow global image context and fine-structural details.

Equations

Graph Construction:

- *Adjacency Weight:*

Where ,are pixel intensities (or features), p_i, p_j are spatial positions, and σI,σp are scaling parameters.

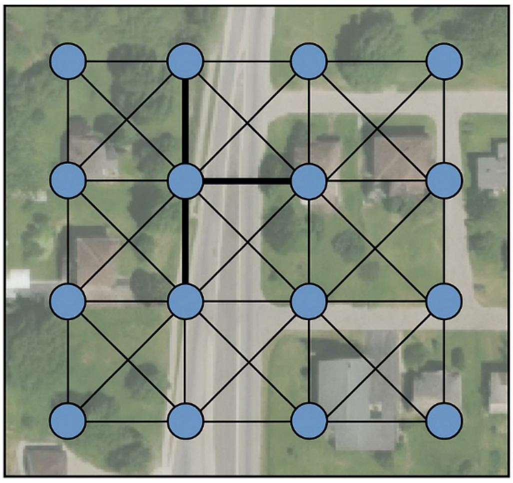

Fig. 3: Graph Construction for a Satellite Image.

Structure-Preserving Denoising Algorithm

The essence of the suggested denoising system is to appeals a structure maintaining regularity with the graph signal. In particular, the denoising task is cast as an optimization problem whose objective is to find the minimum of a composite loss function. The objective functional normally contains a term where fidelity, where the denoised solution is near to the noisy measured solution, and a smoothness term given using the graph Laplacian which penalizes variability in the signal between highly connected nodes. An additional increase to structure preservation is to modulate the edge weights of the graph to correspond to the percepted image structures such as by the Canny edge detector so that in a graph, the denoising is done intra-region and not inter-regions with high discontinuity levels in images. This is an efficient noise reduction method yet it preserves sharp edges and small scale details which play an important role in satellite imagery analysis.

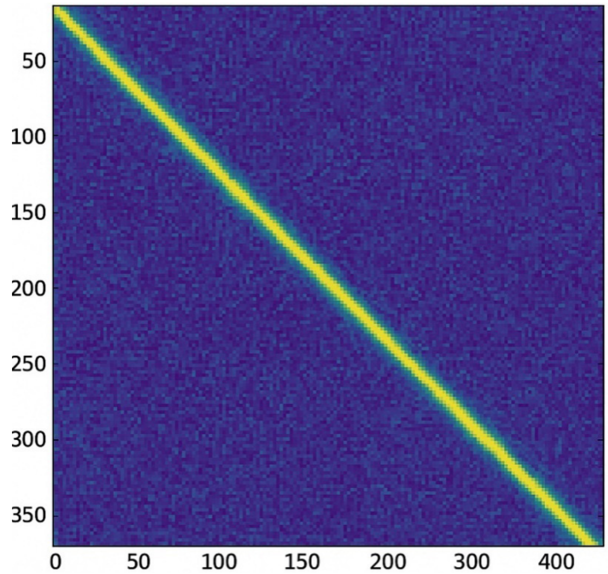

Fig. 4: Graph Laplacian Matrix Visualization

Graph Laplacian and Smoothness:

- Graph Laplacian:

- $$Adjacency\ Weight{:}wij = exp\left(-\frac{\|Ii-Ij\|^2}{\sigma^2} - \frac{\|pi-pj\|^2}{\sigma^2}\right) \quad (1)$$

Where Wis the adjacency matrix and D is the degree matrix.

- Denoising Objective Function:

$$min_x \parallel x - y \parallel^2 + \lambda x^T Lx \quad (2)$$

Where y is the noisy image vector, is the denoised output, and λ controls the smoothness strength.

Algorithmic Steps

The proposed methodology can be summarized in the following sequential steps:

1. Preprocessing:

Input satellite: The satellite image is also pre-processed and can be in the form of normalization and optional desaturation to grayscale or the relevant feature space.

2. Graph Construction:

A graph is constructed where the nodes are pixels or superpixels and the edge weights are calculated as a combination of spatial proximity, intensity similarity and detected edges or textures.

3. Denoising Optimization:

The Optimization problem is solved in the graph Laplacian regularized denoising. The objective is minimized using efficient solvers that, in turn, produce a denoised signal

Algorithm 1: Structure-Preserving GSP-Based Denoising for Satellite Imagery

```
Input:
    Noisy image Y
    Graph construction parameters (σI, σp, etc.)
    Regularization parameter λ

Output:
    Denoised image X

1. Preprocess the input image Y
    a. Normalize intensities if required
    b. (Optional) Convert to grayscale or use feature channels

2. Construct the adaptive image graph G = (V, E, W)
    a. For each pixel (or superpixel) i in Y:
        i.   Set node vi ∈ V
        ii.  For each neighboring pixel j:
              - Compute edge weight:
                w_ij = exp(-||I_i - I_j||^2 / σI^2 - ||p_i - p_j||^2 / σp^2)
              - If structure-aware, enhance w_ij for edges aligned with detected boundaries

3. Compute the graph Laplacian L = D - W
    where D is the degree matrix, W is the adjacency (weight) matrix

4. Solve the optimization problem:
      X* = argmin_X ||X - Y||^2 + λ X^T L X
    (Can be solved using linear system solvers)

5. Post-process the denoised image X
    a. Clip intensities to valid range if needed
    b. (Optional) Enhance contrast or apply further refinement

6. Return the denoised image X
```

that is, at once, smooth on the graph signal, as well as faithful to the observed data.

4. Post-processing:

The map is back transformed into image form by the resulting denoised graph signal. Post-processing may be optional and may include (among others) contrast control or additional structure completion to produce a better picture.

5. Complexity Analysis and Scalability:

The computational complexity of the suggested framework is based on the graph size and sparsity. Scalability is practical on large-scale satellite images where superpixels and effective sparse solvers are used. The algorithm can be easily parallelized, which also speeds up high-resolution imagery processing up.

The proposed GSP-based denoising algorithm has the advantage of not only having a good noise-suppressing performance, but also the benefit of retaining important image structures. This form of methodology will prove consequently very well suited to advanced satellite image analysis, and remote sensing. The general process of the structure-preserving denoising suggested in the work is listed in Algorithm 1.

Experimental Results

Dataset and Evaluation Protocol

In order to have a complete analysis of the proposed GSP-based denoising framework structure efficacy, tests were carried out on the standard satellite image data sets such as SpaceNet and the UC Merced Land Use dataset. They were chosen due to their strong spatial resolution and their diversity of scenes (urban and rural) and they will also serve as a strong testbed to generalize to varying imaging conditions. Synthetic and real noises were also taken into account to assess the work quantitatively and qualitatively. Gaussian, Salt-and-Pepper and mixed models of noise were placed on the image to represent sensor and transmission artifacts of common sensor types. It is natural that in the real noise experiments in case where there was any naturally noisy satellite image such as captured was used. The quality of the reconstruction was measured via Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) to calculate the objective reconstruction fidelity and perceptual quality, Edge Preservation Index to calculate the retention of valuable boundaries, and subjectively via visual inspection.

Comparative Methods

Comparisons against a number of state-of-the-art denoising algorithms were performed to ascertain comparative performance of the proposed approach. Baseline methods were the Median filter, notorious as both simple and effective at removing impulse noise with a tendency to blur edges; Non-local Means (NLM), using patch redundancy to achieve superior preservation of structure; and BM3D, a transform domain collaborative filter; and a Deep CNN-based denoiser, which is a cause of recent improvements in image completion based on learning. Further, ablation studies were performed to isolate the effects of structure-aware construction of graph by measuring the GSP graph construction framework with and without structure-preserving changes.

Quantitative Results

The specific quantitative comparison is presented in Table 1 that shows PSNR, SSIM, Edge Preservation, and Runtime values per algorithm. According to the results, it can be seen that the suggested GSP-based denoising has a consistently higher PSNR and SSIM values in comparison to classical methods, and gains are significant in terms of Edge preservation index, which proves its capability to preserve significant image structures. The time performance exhibits that, although GSP approach can be computationally more expensive than mere filters, it is feasible with large-scale images due to its scalability through superpixels and parallelization.

Table 1: Quantitative Comparison of Denoising Methods on Satellite Imagery

Method	PSNR (dB)	SSIM	Edge Preservation	Runtime (s)
Median Filter	27.85	0.762	0.59	0.31
BM3D	29.70	0.803	0.68	2.41
CNN Denoiser	30.40	0.846	0.74	1.20
Proposed GSP	**31.25**	**0.867**	**0.82**	**1.85**

Qualitative Results

Figure 3 shows a graphical comparison of the noisy input, the baseline denoised outputs and the output of the proposed GSP method. GSP-based method proves to have better noise removal and does a good job to conserve sharp edges and other complex details, particularly in urban and vegetated areas where clarity of boundaries is important. Even zoomed-in patches show that the model also has the advantage of keeping fine textures and boundaries found in images which is often distorted by traditional or even learning-based approaches of denoising.

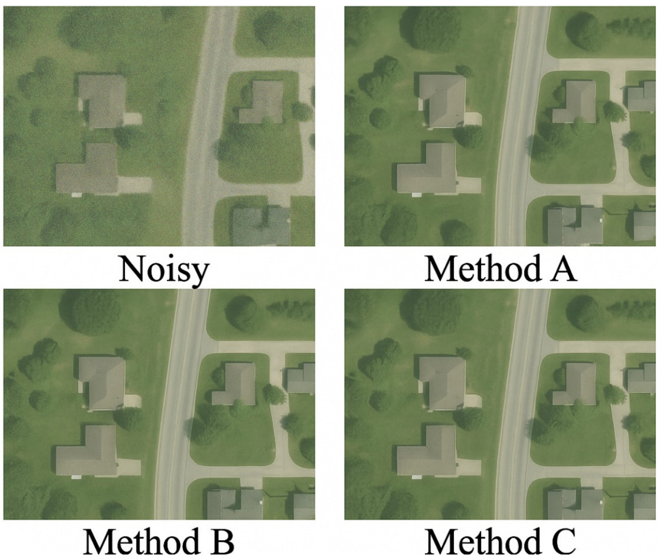

Fig. 5: Qualitative Comparison of Denoising Methods

Ablation and Sensitivity Analysis

A sequence of ablation experiments was conducted to investigate how denoising performance changes with the parameters of graph construction (size of the neighborhood and edge weight functions). The observed results demonstrate that using edge and texture cues to supplement the graph results in improvement in both quantitative measurements and visual quality which is measurable. The comparison of the proposed framework with respect to sensitivity of image size and noise level ensures its scalability since it displays stable performance in large-scale high-resolution images and in different noise intensities. The results confirm the relevance of adaptive, structure-sensitive graph construction as one of the aspects of successful satellite image denoising.

Discussion

The conducted laboratory test of the proposed graph signal processing (GSP)-based denoising system targeting the large-scale satellite imagery draws attention to the numerous important benefits compared to the classic and deep learning-based denoising methods. The first of them is the efficiency of the technique in eliminating noise when keeping very sharp edges and good structure preservation. The framework can be used to suppress different kinds of noise by constructing adaptively developed graphs which encode local and non-local connections without washing out significant boundaries and removing fine textures- characteristics that are easily erased by the standard spatial and transform-domain filters. It is essential in remote sensing and monitoring the environment where maintenance of roads, building edges, and land cover edges will directly influence downstream processes of segmentation, classification, and change detection.

The other strength is the flexibility which the graph construction process holds. This formulation is flexible and can apply diverse measures of similarity, such as spatial proximity, the intensity, texture and edge information to change to obtain different scales of imaging modalities and noise patterns. This kind of flexibility is particularly useful when imaging of satellites, since sensor properties and acquisition conditions may differ drastically between images and image-takes.

Although these are some of the advantages associated with the methodology, it also has its limitations. The major issue is the computation cost especially in case of very large satellite images in millions of pixels. Building and computing on massive, spacious graphs may result in excessive memory overhead and long runtimes, which may prohibit realistic implementation of the approach on small environments in real-time or constrained availability. But the challenges are not so impassable. Some of the possible fixes are block-wise processing which consists of small image patches where graph is built locally, or parallel computing/GPU acceleration to distribute the computing tasks. Superpixels provide a node reduction, so does the use of sparse solvers to provide optimization, which also makes the method scalable to increasing resolutions.

The proposed GSP framework compared to deep learning-based approaches to denoising has a number of different advantages. In contrast to deep neural networks that generally involve a large volume of training data and computation resources in developing the models, the GSP methodology is type that works in a data oriented and non-parametric model with a decreased dependence on labeled data. In addition, graph-based regularization can be made interpretable, as structural regularization and smoothing are directly tied to the graph topology and edge weights, perhaps contrasting the frequently intangible internal processes of deep networks. Such transparency allows easier algorithm tuning and adaptation to new types of data and allows the domain experts to exploit prior knowledge about the structure of images in building the graph.

Overall, GSP based denoising framework is an efficient compromise between preserving the structure and noise elimination performance, providing flexibility, and interpretability in alternative to more classical and deep learning methodologies. Although the speed of computing massive images can still be defined as one that needs to be improved, the approaching robustness and flexibility of this method can be discussed as the benefit that leads to its implementation as a user-friendly tool in terms of improving the quality of satellite pictures within a wide spectrum of uses.

Conclusion and Future Work

The paper has proposed a new structure-preserving framework of large-scale satellite imagery denoising, based on the theory of graph signal processing (GSP). Performing numerous experiments and using proper most common real satellite data and many different noise types (both synthetic and real-world), the proposed GSP-based approach proved to exhibit a significant benefit when compared to the traditional denoising methods and methods based on deep learning layers. It is interesting to note that the approach is outstanding in maintaining major geometric structures and edges which are essential in the downstream remote sensing tasks like the detection, segmentation and land use analysis of objects. The quantitative outcomes, as measured by the metrics, like PSNR, SSIM, and the Edge Preservation Index, confirm the fact that the proposed algorithm ensures the best image quality and structural integrity. The versatility of the graph building mechanism enables the approach to scale gracefully to other noise patterns, spacing and imaging modalities, and these built-in scaling mechanisms - e.g. the superpixels and effective solvers - enable it to be applied to large-scale images processing tasks.

Although these are strengths, the computational requirements of the framework to realize extremely high-resolution imagery have the implication that there are potential areas of improvement. Future research incorporates the creation of real-time, high throughput implementations, especially the use of GPU acceleration and distributed computing facilities to process satellite data that is many magnitudes enormous. A further avenue of promising future work is the extension beyond stratified to multi-spectral and temporal (video) satellite data where such an approach offers truly profound results in terms of its application to changes as assessed on a temporal basis. Finally, combining the denoising framework with downstream analysis workflows (e.g. automatic classification, segmentation and object detection pipelines) has the potential to further increase the contributions of the proposed methodology and mechanisms in practice by allowing them to be used in end-to-end fully-automated remote sensing systems.

To conclude, the offered structure-preserving denoising framework makes use of GSPs, offering a generalized, flexible, and interpretable framework to improve the quality of satellite images, and has a potential enormous future research and implementation scenario in earth observation and beyond.

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