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Hyper Spectral Image Denoising Based On Adaptive Sparse Representation

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ABSTRACT

Hyperspectral images (HSIs) provide rich spectral and spatial information, making them invaluable in various fields such as remote sensing, agriculture, and medical imaging. However, HSIs are often corrupted by noise during acquisition, transmission, or storage, which significantly degrades their quality and usability. This paper proposes an adaptive sparse representation-based approach for hyperspectral image denoising. The method exploits the intrinsic spectral-spatial structure of HSIs and adaptively learns sparse dictionaries tailored to the local characteristics of the data.

By employing an adaptive dictionary learning framework, the proposed method effectively represents the clean signal while suppressing noise. Additionally, spectral correlation across bands is leveraged to ensure consistent denoising without introducing artifacts. The adaptive nature of the sparse representation enables the model to handle diverse noise types, including Gaussian, impulse, and mixed noise. Experimental results on synthetic and real-world datasets demonstrate that the proposed method outperforms state-of-the-art denoising techniques in terms of both quantitative metrics (e.g., PSNR, SSIM) and visual quality. The findings highlight the potential of adaptive sparse representation for improving hyperspectral image quality in practical applications.

1-INTRODUCTION

This chapter offers a fundamental overview of remote sensing and its application. It describes the hyperspectral (HS) imaging, types of hyperspectral imaging, and hyperspectral image denoising (HSI-D). It provides the generalized process of HSI-D based on machine and deep learning (DL). Further, the concise problem statement along with research objectives creates the foundation for the proposed research.

Remote Sensing

Remote sensing is a technique for gathering data about a target or phenomena without real physical touch, enables us to collect information from inhospitable and perhaps dangerous places. Space- and airborne-based remote sensing are the two primary forms of remote sensing. An electronic gadget called a remote sensor finds electromagnetic radiation, measures it, and frequently records the information in analogue or digital form. There are two kind of remote-sensors passive and active.

2-LITERATURE SURVEY

A comprehensive assessment of the literature is provided in this chapter on various machine and DL techniques for the HSI-D. It provides the methodological details, pre- processing techniques, dataset, evaluation metrics, advantages, disadvantages and future challenges. Further, it provides the research gaps identified from the survey and paves the way for consideration of problem statement and objectives.

Survey of ML based HSI-D

The use of HS remote sensing technology, it blends the variety of ground objects—whose particular material composition determines their shape, texture, and arrangement—with the spatial picture that reflects them makes it possible to accurately detect, identify, and analyse the attributes of earthly things. The HSIs that follow include a wealth of spectral data that represents the distinctive physical characteristics of ground features as well as spatial information that reflects those attributes. Thus, HSIs may be used to address problems like each pixel's exact identity that multispectral or natural images are unable to resolve. Due to the fact that various materials are displayed different spectral features, the effectiveness of HSI for categorising materials may be more accurate. These benefits have prompted the widespread use in HS remote sensing several applications such crop monitoring, land resources, and precision agriculture. In order to safeguard the environment, Gas, oil spills, water quality, and have all been detected using HSI and plant covering to better preserve our living environment. Human skin health has been evaluated in the medical field using HSI skin testing.

The generalized process of the machine learning based HSI-D, In Figure 2.1, this is shown. The generalized flow diagram of the ML based HSI-D encompasses preprocessing, feature extraction and classification. It generally includes training (TRN) and testing (TTE) phase. In the training phase the tagged data is used for the training of the classifier using the raw data or the features of the HSI.

Survey of DL based HSI-D

DL technology has advanced quickly and sparked a great deal of attention during the past ten years. DL technology can automatically discover patterns from data, unlike traditional machine learning algorithms, wHSI-Dh need feature patterns to be constructed on purpose. As a result, it has achieved exceptional performance and been effectively implemented in the fields of object detection, voice recognition, semantic segmentation, autonomous driving, in addition to natural language processing. A recent delivery of it to the area of HSI categorization as well. The status of the art at the moment allows for the classification of all approaches according to the combined spatial-spectral feature into the Two-Stream and Single-Stream categories, depending on whether the combined spatial and spectral characteristic is concurrently extracted. Spectral (SPE) and spatial (SPA) branches are often included in the construction of two-stream systems. The first is used to determine the pixel's spectral properties, while the second is used to record the SPA relationships between the core pixel and its surrounding pixels. Furthermore, each and every DL module, including the the recurrent unit, the fully connected layer, and the convolutional layer, has been covered by the currently available techniques. The suggested HSI-D is implemented using the Indian Pines (IPs) and Salinas datasets (SDs). Due to the restricted availability of HS datasets, several studies have employed 30% to 70% of the available pixels for training. For TRN and TTE purposes, the HS patches Optimal denoising minimizes the code length of the image under the model Sparse coding + dictionary learning viewed as data compression Orthogonal Matching Pursuit (OMP): A greedy algorithm that iteratively selects the most correlated atoms from the dictionary to represent the image The OMP algorithm has several desirable properties Exact recovery Under certain conditions, OMP can recover the exact sparse signal Robustness to noise OMP can tolerate some level of noise in the measurements. Computational efficiency OMP has a relatively low computational complexity compared to other sparse recovery algorithms.

representation of the image. SBL is based on Bayesian inference, which provides a probabilistic framework for modelling uncertainty. The goal of SBL is to infer the sparse representation of a signal or the relevant features of a dataset Sparse prior A prior distribution is placed on the model parameters, which encourages sparsity. Likelihood The likelihood function models the relationship between the observed data and the model parameters.

3-OVERVIEW OF TRADITIONAL METHODOLOGY

This chapter describes the overview of the traditional methodology in details. It provides the information regarding database, evaluation metrics, simulation configurations and overview of the traditional methodology. It creates the background the system simulation and implementation of the traditional system.

Dataset

The suggested HSI-D is implemented using the Indian Pines (IPs) and Salinas datasets (SDs). Due to the restricted availability of HS datasets, several studies have employed 30% to 70% of the available pixels for training. For TRN and TTE purposes, the HS patches are divided at a ratio of 70:30. The dataset details are mentioned as follow:

Indian Pines

The dataset for Indian Pines (IPs) is the collection of information that is gathered by IVIRIS sensors at the IP location in Indiana, United States. The HSI pictures include 145 by 145 by 220 spectral bands, each of which was recorded at a distinct wavelength spanning from 0.4 micrometers to 2.5 micrometers. One third of the land is devoted to agricultural use, while the other third is forested and covered with natural flora. In addition, it consists of two lanes of a highway, a number of low-density housing units, a rail line, other minor roads, and other man-made buildings. The depiction of several sample spectral bands taken from the IPs dataset may be seen in Figure 3.1. As the figure shows it has been discovered that the IPs dataset has a large amount of duplicated spectral bands as well as bands that provide less information.

Salinas

The SD is made up of HS pictures that were collected over the Californian Salinas Valley. These images have a resolution of 512 by 217 pixels and include 224 bands. It consists of sixteen different classifications of uncultivated land, including vegetable and vineyard areas.

4-HYPERSPECTRAL IMAGE DENOISING USING PRINCIPLE COMPONENT ANALYSIS

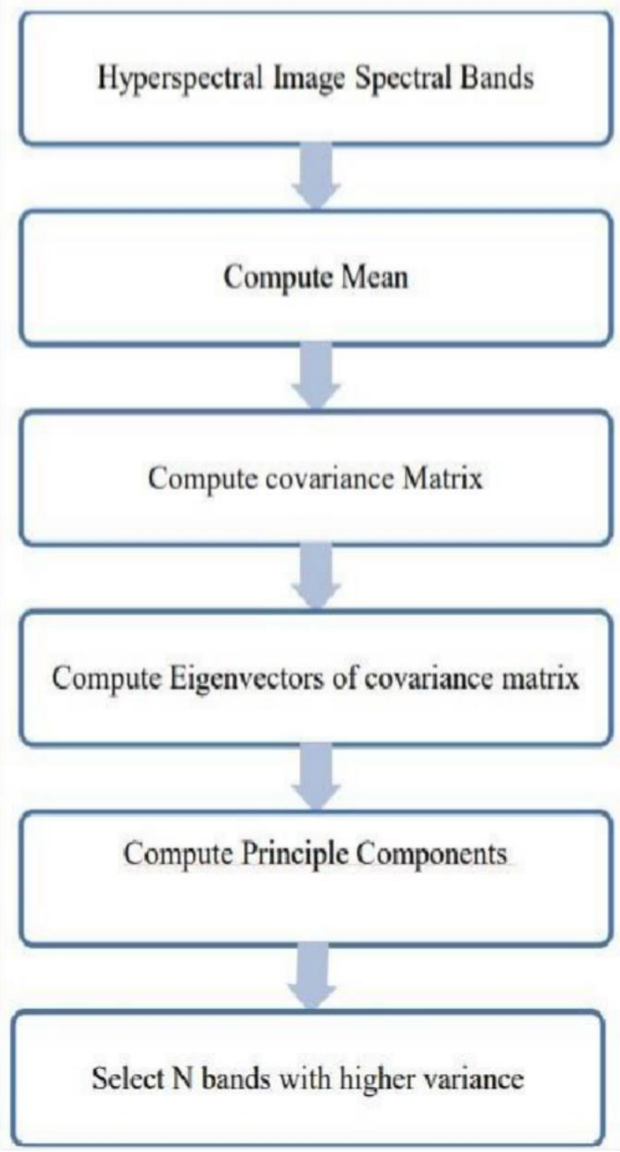
This chapter describes the implementation of the HSI-D using PCA. It provides the detailed information regarding PCA architecture, parameter configurations, layers information, implementation system details, results and discussion on the results.

Fig.4.1 Process of proposed HSID using PCA

Channel Selection using PCA

One of the most often utilised techniques in multivariate analysis is principal component analysis. It is frequently utilised in areas like as financial forecasting, neural computing, statistical analysis, and signal processing. The principle component (PC), which is sorted from the most variant basis to by the principal component analysis (PCA). The majority of the variance included in the entire original data set will thus be retained by the first few primary components. The IPs dataset consists of total N spectral bands.

Channels must be chosen lowering the complexity of computing and timing, with the majority of the data present



in all n variables will be contained with m << n. The process of spectral band selection using PCA is demonstrated in Figure 4.2.

Fig.4.2 Steps to implement PCA algorithm for spectral band selection

The hyper spectral data (XX) is arranged in k matrix where n stands for number of bands in each HSI signal.

5-HYPERSPECTRAL IMAGE CLASSIFICATION USING BASED ON ADAPTIVE SPARSE REPRESENTATION

This chapter provides the HSI-D based on Adaptive Sparse Representation which provides improved HSI-D results and minimized computational complexity of the network. It provides the detailed information regarding for the ASR and improved ASR spectral (SPE) band selection of the HIS. Further, it gives elaboration of the proposed LCDCNN architecture. Hyper spectral image classification using adaptive sparse representation involves representing each pixel in the image as a sparse linear combination of atoms from a dictionary. The dictionary is learned adaptively from the training data, and the sparse coefficients are used as features for classification.

Next, subsection depicts the experimental results and the findings from the results.

Adaptive Sparse Representation

The original IPs and SD consists of many redundant spectral bands and spectral bands with irrelevant information. The advantages of the spectral band reductions are summarize as follow:

- It increases the system's accuracy.
- It decreases the computational complexity inside the system.
- It helps to reduce the over-fitting

ASR helps to analyze the relationship between the HIS's many spectral bands. ASR provides the new subspace that represents the features with high variance in multidimensional data. A way for reducing the number of dimensions is the adaptive sparse representation also known as normal adaptive sparse analysis or adaptive sparse function analysis frequently employed for issues with supervised categorization. It is used to show how groups differ from one another by dividing groupings into two or more classes. This approach projects the properties of a realm of larger dimensions above a space of lower dimensions. ASR works on two principles such that minimizing the difference between same class bands the inter-class and maximization of intra-class between two separate classes. The algorithm for the ASR based spectral band selection is represented as follow:

Algorithm: ASR based spectral band selection

Suppose $T = \{T1, T2, T3, \dots \dots \dots TT\}$ are the N spectral bands presents for the every class sample.

Results on Synthetic data

The synthetic data are obtained from the AVIRIS (airborne visible/infrared imaging spectrometer) Sandiego Airport scene. The original data has 400 400 × pixels and 224 spectral channels with atmospheric correction. A high-quality subset of size 200 200

96 × × is used for our experiments as the clean image and each band is normalized to [0, 1] in advance. To evaluate the denoising performance of the proposed HyDeASp, a zeromean Gaussian noise is added to the clean HSI data and different band images are given different noise levels per the assumption that the noise levels vary band by band. The signal-to-noise (SNR) index, the peak signal-to noise (PSNR) index and the structural similarity (SSIM) index are calculated for quantitative assessment of the different denoising approaches performance. We define these indexes as

where s is the clean HSI data cube, sˆ is the reconstructed HSI data cube. The size of s is M × × N L , and its indexes are i jl , , . The SNR and PSNR measure the degree of overall approximation of the denoised HSI to the clean image Effective Noise Removal: NCTV has demonstrated its ability to effectively remove mixed noise from hyperspectral images, including Gaussian, impulse, stripe, and dead-line noise. This is combined with gradient preservation of Image Details: The proposed method has shown improved performance in preserving image details during the denoising process, leading to enhanced overall quality.

indicate that it outperforms them in terms of detail retention the rank of the matrix. Comparison with State-of-the-Art Techniques: NCTV has been compared with existing algorithms, and the results indicate that it outperforms them in terms of detail retention and noise removal. images to construct a novel regularization Details: The proposed in the NCTV approach involves introducing a non-convex function to more accurately approximate the rank of the matrix. This is combined with gradient information of hyperspectral images to construct a novel regularization term. The proposed method effectively combines low-rank and local smoothness priors, leading to improved denoising performance. These findings suggest that adaptive sparse representation methods, such as NCTV, can be effective in hyperspectral image denoising, especially when dealing with synthetic data.

6-OUTPUT AND RESULTS

Hyperspectral image (HSI) denoising based on adaptive sparse representation is a highly effective approach that leverages the inherent low-rank and sparse nature of HSIs, along with their strong spatial and spectral correlations, to accurately remove noise while preserving critical image details. The "adaptive" aspect, where the dictionary used for sparse representation is learned from the noisy data itself, is crucial for achieving superior performance across various noise types and image content.

Output of Adaptive Sparse Representation Denoising

The output of an HSI denoising process based on adaptive sparse representation is a denoised HSI cube that aims to be a close approximation of the original, noise-free HSI. This output generally exhibits:

- Reduced Noise: Significant attenuation or removal of various noise components (e.g., Gaussian, impulse, stripe, deadlines), leading to a cleaner and more visually appealing image.
- Preserved Spatial Details: Edges, textures, and fine spatial structures within each band are largely maintained, preventing over-smoothing that can occur with simpler denoising methods.
- Maintained Spectral Fidelity**:** The unique spectral signatures of different materials are preserved, which is critical for downstream tasks like material identification, classification, and unmixing. Adaptive methods minimize spectral distortion, ensuring that the spectral curves of pixels remain consistent with their true properties.
- Improved Visual Quality**:** The denoised images appear sharper, clearer, and more natural, enhancing human interpretability.

Results and Performance Evaluation

The effectiveness of adaptive sparse representation methods for HSI denoising is typically evaluated using both quantitative metrics and qualitative (visual) assessments.

Quantitative Metrics:

These metrics provide objective measures of denoising performance by comparing the denoised HSI with a ground truth (noise-free) HSI, which is often simulated by adding known noise to a clean image.

1. Peak Signal-to-Noise Ratio (PSNR):

Measures the ratio between the maximum possible power of a signal and the power of corrupting noise. Higher PSNR values indicate better denoising performance.

For HSIs, Mean PSNR (MPSNR**)** across all bands is commonly reported.

Formula: PSNR=10.log10(MSEMAXI2), where MAXI is the maximum pixel value and MSE is the Mean Squared Error between the original and denoised image.

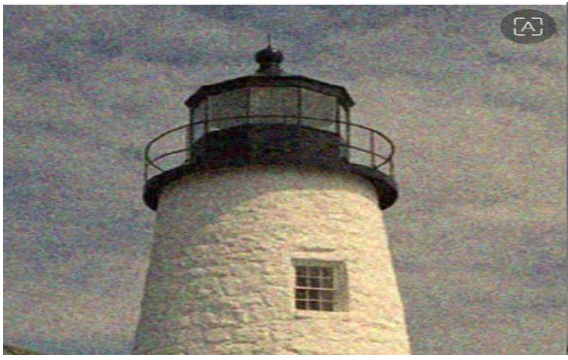
2. Structural Similarity Index Measure (SSIM): Evaluates the similarity between two images based on luminance, contrast, and structure. Values range from -1 to 1, with 1 indicating perfect similarity.

Mean SSIM (MSSIM) across all bands is often used for HSIs.

SSIM is often preferred over PSNR as it aligns better with human visual perception.

PHASE 1 OUTPUT

NOISY IMAGE



DE NOISY IMAGE

PHASE 2 OUTPUT

NOISY IMAGE

RECONSTRUCTED DENOISY IMAGE

CONCLUSION

In this paper, we propose a novel denoising method for HSI, termed HyDeASp, which is based on the theory of sparse coding extended to the spectral domain to make full use of spectral information. Both online spectral dictionary learning and sparse coding is done in the spectral domain. Compared with several existing HSI denoising algorithms, such as band by band wiener, DWT, BM3D and MTSNMF, HyDeASp yields similar of better performance and can well preserve the intrinsic details of both spectral and spatial structures when significantly denoising. This characteristics put the proposed HyDeASp in a leading position to be used as an HSI denoiser.

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