An Approach towards Improved Hyperspectral Image Denoising

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Abstract: ***Amount of noise included in a hyperspectral image limits its application and has a negative impact on hyperspectral image classification, unmixing, target detection, and so on. The data that are contaminated with noise can cause a failure to extract valuable information and hamper further interpretation. The presence of noise in the image, extraction of all the useful information becomes difficult and noise can lead to artifacts and loss of spatial resolution. So to overcome this problem there should some method/system which removes noise to improve performance of subsequent application. It has been proved that the proper and joint utilization of global and local redundancy and correlation (RAC) in spatial/spectral dimensions gives better result in HSI denoising. Thus for removing noise we are going to use proper and joint utilization of global and local redundancy and correlation (RAC) in spatial/spectral dimensions and data representation scheme as sparse representation to capture local and global RAC in spatial and spectral domains. Especially it uses local RAC in the spectral domain and global RAC in the spatial domain which utilized in the framework of sparse representation. Here we can use image patches of few continuous bands with dictionary learning from the noisy HSI. In this case spectral distortion will introduce in global RAC, to reduce this proper regularization of low rank is helpful which make ill-posed denoising problem solvable. The low rank of HSI is also helpful to reduce error by enforcing low rank on the denoised data, which is introduced in the process of sparse coding and dictionary learning.***

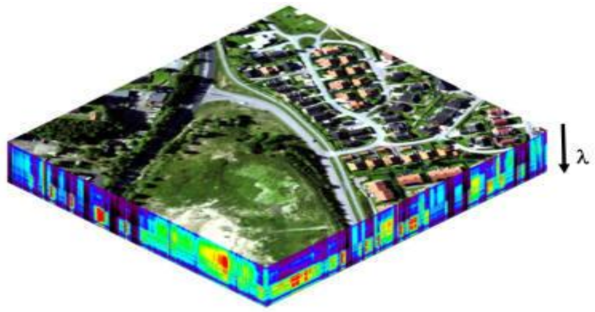
Keywords: Hyperspectral image (HSI) denoising,Global redundancy and correlation (RAC), local RAC, low rank, sparse representation.

1. Introduction

Denoising is simply the removal of noise points from an image by smoothing it out with respect to its surrounding pixels. In general denoising can called a method of estimating the unknown signal from available noisy data. Hyperspectral imaging (HSI) has many applications in agriculture, diagnostic medicine, and military surveillance, satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. It also useful in many applications such as environmental modeling and assessment for Earth-based and atmospheric studies, risk/hazard prevention and response including wild land fire tracking, biological threat detection, monitoring of oil spills and other types of chemical contamination, target detection for military and defense/security purposes, urban planning and management studies, etc. In those application data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. The reliability of the information delivered by these digital images in above referred applications highly depends on the quality of the captured data. Increasing image quality by the improvement of imaging spectrometer and instrument system is prohibitively expensive, especially in airborne instrument. Hence, hyperspectral data denoising method has been taken into account.

Hyperspectral deals with imaging narrow spectral bands over a continuous spectral range, and produce the spectra of all pixels in the image/scene . Hyperspectral imaging is part of a class of techniques commonly referred to as spectral imaging or spectral analysis. Most images contain only data in the color spectrum. Hyperspectral images contain data from several, continuous wavelengths. These images can be thought of as being stacked on top of each other, creating an image cube, having two spatial dimensions and a third spectral dimension. This creates a pixel vector; the vector can be used to classification of one material from another. HSI also called as imaging spectrometry are a systems technology whereby images of a scene are collected in tens to hundreds of narrow spectral bands nearly simultaneously. Every pixel in the image thus contains a continuous spectrum (in radiance or reflectance) and can be used to characterize the objects in the scene with great precision and detail. Processing techniques generally identify the presence of materials through measurement of spectral absorption features.

To date, many different denoising methods have been proposed for the restoration of HSIs. State-of-the-art denoising methods treat each band of the HSI as a gray-level image and restore them separately. More advanced denoising techniques mainly use the spectral information of the HSI and have achieved good results.



HSI cube

The most popular method is principal component analysis (PCA) denoising, which retains the first few principal components (PCs) containing most of the information and discards the rest of the PCs which contain little information and are assumed to be noise. In [1] proposes a hyperspectral image denoising algorithm employing a spectral–spatial adaptive total variation (TV) model, in which the spectral noise differences and spatial information differences are both considered in the process of noise reduction. The spatial and spectral views are fused using a metric *Q*-weighting strategy in [2], to improve performance of denoising. Some methods achieve denoising with transforming each band HRSI into curvelet domain [15]. A noise reduced HSI can obtain by[16] combining the rank-1 tensors using an eigenvalue intensity sorting and reconstruction technique and some methods focus on spatial and spectral correlation and sparse approximation etc. It has been found that in the hyperspectral images, thus these images are remotely sensed there is much correlation and redundancy in spatial and spectral view.

If efficient approximation of this RAC is used it can achieve great performance in terms of denoising. To achieve this data representation scheme is uses as sparse representation to capture local and global RAC in spatial and spectral domain. In this dictionary can be learned by utilizing RAC in an image. A noise-free image can be sparsely approximated by dictionaries'atoms, whereas a noisy image cannot be sparsely approximated due to noise's stochastic nature. The denoised image is estimated using linear combination of atoms or bases. This type of representation can compute global RAC in spatial dimension and local RAC in the spectral dimension. If RAC in whole spectral dimension is exploits, learned dictionary becomes more accurate and HSI reconstructed with less error. The rank of noisy component is usually full and no correlation found among noise components in different band due to noise is in stochastic nature. Large spectral distortion will be caused if RAC in whole spectral dimension is not considered. To overcome this shortcoming low rank constraint is added. Low rank is used to remedy the deficiency of sparse representation in spectral information utilization.

Noisy and Denoised Image

2. Literature Survey

The search for good image denoising methods is still a valid challenge at the crossing of functional analysis and statistics. In spite of the sophistication of the recently proposed methods, most algorithms have not yet attained a accurate level of applicability. The simplest way of HSI denoising is to utilize traditional 2-D or 1-D denoising methods to reduce noise in HSI band by band or pixel by pixel. But this method does not give accurate result (close to actual images) it only removes spatial or spectral domain noise. Thus artifacts and distortion can introduce in other domain and these kinds of methods destroy the correlation in spatial or spectral domain.

A hyperspectral image is usually viewed from the front, which is the spatial view. However, a hyperspectral image, if viewed from the side direction, will also have a spectral view. For a hyperspectral image, noise not only exists in the spatial view but also in the spectral view. In most hyperspectral image denoising methods, the hyperspectral image is just denoised from the spatial view, ignoring the role of the spectral view. In paper [1], author proposes an HSI denoising algorithm by utilizing the local and global RAC in spatial and spectral domains jointly. Global RAC in the spectral domain is utilized by the regularization of low rank. Therefore, in [2] paper, it propose a spatial–spectral view fusion algorithm for hyperspectral image denoising. A noisy hyperspectral image is first denoised using the hyperspectral total variation (TV) approach proposed in previous work, from both the spatial and spectral views, and then the denoising results of the two views are fused using a metric *Q*-weighting strategy.

In [5] propose image denoising as a simple physical process, which progressively reduces noise by deterministic annealing. The results of implementation are numerically and visually excellent. It further demonstrates that our method is particularly suited for synthetic images. Finally, offer a new perspective on image denoising using robust estimators. This method produces high-quality results, void of artifacts typical to patch-based methods. It performs not only well for natural images, but also for synthetic images where artifacts are more apparent. It is also of practical interest that algorithm is unusually short, fitting into a column of this paper.

Some denoising methods rearrange the HSI data 3-D to 2-D data and ignores the spectral relationship in different bands of images. A hyperspectral image (HSI) is always modeled as a three-dimensional tensor, with the first two dimensions indicating the spatial domain and the third dimension indicating the spectral domain. The tensor decomposition method has been adopted to denoise hyperspectral image, for instance Tucker3 called three-mode factor analysis model. This type of model has problem with uniqueness of decomposition and in multiple ranks estimation. To overcome this problem [8] introduces a powerful multi-linear algebra model, named parallel factor analysis (PARAFAC), and thus number of estimated rank is reduced to one.

To achieve hyperspectral image denoising some techniques are employed to get better and improved image denoising as close to as original image. These techniques are for example, an HSI was treated as a hypercube in order to take into account the correlation among different bands [13]; tensor-algebra was brought to jointly analyze the 3D HSI, PCA (principle component analysis) for inter-band correlation and dimensionally reduction [14], a combination of spatial and spectral wavelet shrinkage used to catch dissimilarity of signal nature in spatial and spectral dimensions [9]. The method in [15] achieves denoising with transforming each band HRSI into curvelet domain. A noise reduced HSI can obtain by[16] combining the rank-1 tensors using an eigenvalue intensity sorting and reconstruction technique and some methods focus on spatial and spectral correlation and sparse approximation etc.

To maintain image details in low-noise-level case,the noise in the spectral domain was increased by using spectral derivative, and then, wavelet-based spatial and spectral denoising was implemented [9].

3. Methodology

In presence of noise in the image, extraction of all the useful information becomes difficult and noise can lead to artifacts and loss of spatial resolution. So to overcome this problem there should some method/system which removes noise to improve performance of subsequent application.

Removing noise for HSI under strong noise condition is the main aim of this system. However, in the real case, the noise level varies with the change of spectral band. Strong noise refers to that where more artifact, reduction of spectral unmixing, edges blurring so difficult to identify objects, distortion exists which degrade the data of interest.

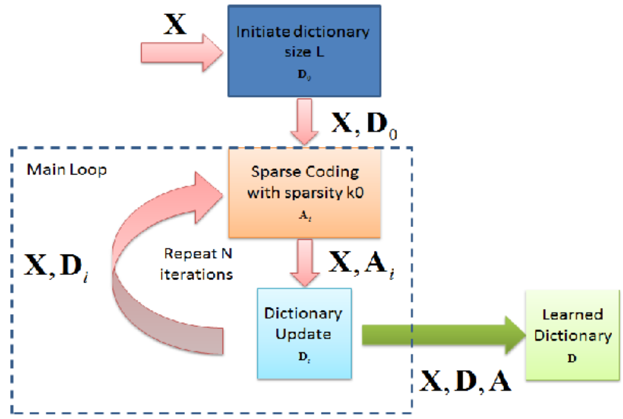
It has been proved that the proper and joint utilization of global and local redundancy and correlation (RAC) in spatial/spectral dimensions gives better result in denoising. Hyperspectral data is significantly redundant because (i) its layers (one at each wavelength) are highly correlated and (ii) similar to 2D images, the pixels in each of its layers are geometrically correlated. For removing noise we are going to use data representation scheme as sparse representation to capture local and global RAC in spatial and spectral domains. Sparse representation is widely believed to bring many benefits to classification problems in terms of robustness and discriminativeness. Specifically, sparsity is a regularizer that can reduce the solution space under ill-conditioned problems, by seeking to represent a signal as a linear combination of only a few bases. These bases are called the "atoms" and the whole over complete collection of atoms together form what one call a "dictionary". Many natural signals such as image and audio indeed have sparse priors. Imposing sparsity not only returns a unique solution, but also helps to recover the true signal structure, giving more robust estimation against noise. In addition, the sparse representation of a signal often leads to better separation and de-correlation which benefits subsequent classification problems.

Dictionary Learning is a topic in the image/signal processing area, the dictionary is usually used for Sparse Representation or Approximation of signals. A dictionary is a collection of atoms; here the atoms are real column vectors of length N. A finite dictionary of A atoms can be represented as a matrix D of size NxA. A common setup for the dictionary learning problem generally starts with access to a training set, a collection of training vectors, each of length N. This training set may be finite, and then the training vectors are usually collected as columns in a matrix X of size NxL, or it may be infinite. For the finite case the aim of dictionary learning is to find both a dictionary, D of size NxA, and a corresponding coefficient matrix W of size AxL such that the representation error, R=X-DW, is minimized and W fulfill some sparseness criterion.

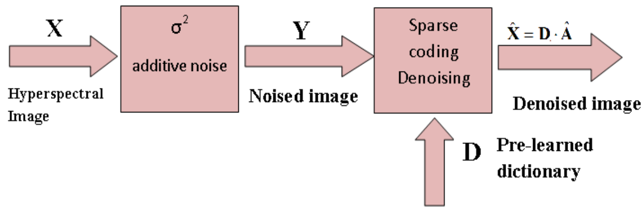
The rank is also the dimension of the image of the linear transformation that is given by multiplication by matrix M. More generally, if a linear operator on a vector space (possibly infinite-dimensional) has finite-dimensional image (e.g., a finite-rank operator), then the rank of the operator is defined as the dimension of the image.

The paper uses local RAC in the spectral domain and global RAC in the spatial domain which utilized in the framework of sparse representation. Here we can use image patches of few continuous bands with dictionary learning from the noisy HSI.

In this case spectral distortion will introduce in global RAC to reduce this proper regularization of low rank which make ill-posed denoising problem solvable. In process of sparse coding and dictionary learning error can introduced, the low rank of HSI is in is helpful to reduce these errors by enforcing low rank on the denoised data.



Dictionary Learning Flow



Sparse coding denoising

Thus here proposed project plan is preparation of sparse matrix for hyperspectral image. Then it will evaluate of global and local thresholds\data from the sparse matrix. Denoise the given image in spatial and frequency (spectral) domain. If efficient approximation of this RAC is used it can achieve great performance in terms of denoising. To achieve this data representation scheme is uses as sparse representation to capture local and global RAC in spatial and spectral domain. In this dictionary can be learned by utilizing RAC in an image. A noise-free image can be sparsely approximated by dictionaries' atoms, whereas a noisy image cannot be sparsely approximated due to noise's stochastic nature. The denoised image is estimated using linear combination of atoms or bases. Large spectral distortion will be caused if RAC in whole spectral dimension is not considered. To overcome this shortcoming low rank constraint is added. Low rank is used to remedy the deficiency of sparse representation in spectral information utilization. The rank of noisy component is usually full and no correlation found among noise components in different band due to noise is in stochastic nature. For optimization purpose or to simplify the solving process we will use here genetic optimization technique in our last step. All the work on Genetic algorithm based denoising is done based on normal images, but here we are doing same for HSI. Proposed system is distributed in module such as Image Dataset collection, Evaluation of region of convergence, Preparation of Sparse Matrix for image, Evaluation of global and local thresholds from this sparse matrix, Denoising image in spatial and frequency domain, evaluating image parameters like PSNR, MMSE and Time. For optimizing computational task we are using here optimization technique for better result in achieving comparative indexes and achieving output image as close to as original image. Once the image has been denoised completely, we would be performing soft computing techniques, genetic optimization to optimize the denoising process.

The system aims to reduce time complexity in achieving improved denoising of hyperspectral image than other existing methods. So this system should accelerate the speed than other existing methods and improves the computational cost. Thus images should recover fast and accurately

Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) as well as in terms of visual quality of the images. In reality, this assumption may not always hold true due to the varied nature and sources of noise. An ideal denoising procedure requires a priori knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms. The assessing indexes normally used are peak signal-to-noise ratio (PSNR), structural similarity index measurement (SSIM), and feature similarity index measurement (FSIM). These two indexes are designed based on human's visual characteristic. Index value is higher; denoised image is more similar to the original image in human's vision sense. So the in this all the indexes PSNR, SSIM, and FSIM will improved.

4. Conclusion

Study says that Hyperspectral imagery will be a very powerful tool for characterizing the components of the observed scenes. In process of capturing and transmitting the hyperspectral data transmission media, noises are unavoidable introduced, and affect the post-processing of hyperspectral image, such as classification and target detection. Three major objectives in processing hyperspectral image data of an object (target) are data compressive representation, spectral signature identification of constituent materials, and determination of their corresponding fractional abundances. Hyperspectral data is typically noisy and suffers for both spatial and spectral blurring. Denoising is simply the removal of noise points from an image by smoothing it out with respect to its surrounding pixels.

Due to correlation and redundancy exist among different dimension of HSI. If these things considered jointly better performance would obtain. In this paper, we have proposed an HSI denoising method by jointly utilizing local/global RAC of HSI in spatial and spectral domains. Global RAC in spatial dimension is exploited via dictionary learning in the framework of sparse representation. However, only local RAC in spectral dimension could be used in the sparse representation framework. Large spectral distortion will be caused if global RAC in spectral dimension is not employed. In order to take advantage of global RAC in spectral dimension, low-rank constraint is added as regularization. The rank of noise-free HSI data is expected to be low due to high RAC among images in different bands, while the rank of noisy data is full. We add the rank of noise-free HSI as regularization in the objective function to force it to be low to exploit the global RAC in spectral dimension and it is helpful to reduce error by enforcing low rank on the denoised data, which is introduced in the process of sparse coding and dictionary learning. This approach gives us an opportunity to improve the data quality in order to allow remote sensing applications to deliver better final products.

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