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Denoising Hyperspectral Images Using Multijoint Method of Filter Estimation

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Abstract: *Denoising the hyperspectral images (HSIs) which include both signal-dependent (SD) and signal-independent (SI) noise from signal. The signal dependent noise such as electron noise due to the electrical fluctuation in the current. The photon noise occurred during calibration process. The noise removed by using various methods. To denoise HSIs distorted by both signal-dependent (SD) and signal-independent (SI) noise, some hybrid methods, which reduce noise by two steps. The first one, named as the PARAFAC SI –PARAFAC SD method. The second one is the HYperspectral Noise Estimation (HYNE) method and PARAFAC decomposition, which is named as the HYNE-PARAFAC method. The last one combines the Wiener filter (MWF) method and PARAFAC decomposition and is named as the MWF-PARAFAC method. However, conventional hyperspectral imaging suffers from limited light in individual bands which introduces noise into the imaging process. In this paper, we present a simple but effective denoising method that exploits the spectral domain*

Index Terms: *Denoising, hyperspectral image (HSI), PARAFAC, signal-dependent (SD) noise, signal-independent(SI), Multidimensional Wiener Filter(MWF).*

I. Introduction

This document is based on Hyperspectral image which consist of hundreds of bands in the spectral. The several bands in the image called tensor. The noise in HSIs can be classified into two method which include random noise and photon noise. The random noise comes from signal dependent and signal independent noise.

Military and civilian applications involve the detection of an object or activity such as a military vehicle or vehicle tracks. Hyperspectral imaging sensors provide image data containing both spatial and spectral information, and this information can be used to address such detection tasks. Hyperspectral imaging sensors measure the radiance of the materials within each pixel area at a very large number of contiguous spectral wavelength bands. In a passive remote sensing system the primary source of illumination is the sun. The distribution of the sun’s emitted energy, as a function of wavelength throughout the electromagnetic spectrum, is known as the solar spectrum.

Thus, we can deduce that tensor decomposition will be an important issue when analyzing tensors. We can define different decompositions that represent different approaches to the various problems that arise when studying tensors. In this report we will consider the generalization of the Singular Value matrix Decomposition (SVD) to higher order arrays which correspond to the Higher Order Singular Value Decomposition (HOSVD) on one hand, and the CANDECOMP/PARAFAC decomposition (canonical decomposition and parallel factor decomposition respectively) on the other hand. These two decompositions are connected with two different tensor generalizations of the concept of matrix rank.

The CANDECOMP/PARAFAC decomposition rewrites a given tensor as a sum of several rank 1 tensors. To denote a tensor to be of rank 2 if it can be expressed as the sum of two rank 1 tensors. Similarly, define a tensor to be rank 3 if it can be expressed as the sum of three rank 1 tensors. Definition the rank of a tensor T is the minimal number of rank 1 tensors that yield T as a linear combination.

To denoising of white Gaussian noise (WGN) and Canonical Decomposition/Parallel Factor Analysis (CANDECOMP/PARAFAC) had been successfully applied in the reduction of WGN[12],[13], we propose to reduce SI noise by PARAFAC decomposition, the HYNE method, or the MWF method first. Then, the residual SD components can be further reduced by PARAFAC decomposition method.

AVIRIS is a unique optical imaging sensor that delivers calibrated images of the upwelling spectral radiance in 224 contiguous spectral channels with wavelengths from 0.4 to 2.5 µm. The main objective of the AVIRIS project is to identify, measure, and monitor constituents of the Earth's surface and atmosphere based on molecular absorption and particle scattering signatures. Higher spatial resolution AVIRIS data have become available in recent years as the system has been reconfigured to allow flight on low-altitude aircraft, particularly flying at 4 km above ground level at 130km/hour.

The two well-known 2-D denoising methods, i.e., minimum noise fraction (MNF) and noise-adjusted principal components analysis (PCA) [8]. The proposed methods are efficient in the reduction of both SI and SD noise in HSIs. Therefore, here hybrid methods are proposed: the PARAFAC SI –PARAFAC SD method and the HYNE-PARAFAC method and the MWF-PARAFAC method, which combines the MWF method and PARAFAC decomposition. If the SI noise is colored, we also prove that the HYNE method and PARAFAC decomposition can effectively remove this colored SI noise. Hence, the proposed HYNE-PARAFAC and PARAFAC SI –PARAFAC SD methods can denoise HSIs distorted by both SD and white or colored SI noise.

II. Multilinear Algebra Tools

Tucker3 decomposition is a form of higher-order PCA, and it decomposes a tensor into a core tensor multiplied by a matrix along each mode. Thus, it is necessary to estimate multiple ranks for Tucker3 decomposition, which leads to the nonuniqueness of this decomposition.The multidimensional Wiener filtering method is an extension of the subspace-based approach to the multidimensional case based on Tucker3 tensor decomposition and Wiener filter. However, the MWF method also has the nonuniqueness characteristics and needs to estimate multiple ranks as Tucker3 decomposition.

Principal components analysis (PCA) is a versatile technique and has been used widely in signal processing for various applications such as dimensionality reduction, data compression, and feature extraction. It is of particular interest in multispectral image processing, because it can be used to decorrelate spectral correlation. The variance of multispectral images did not necessarily reflect real SNR, due to unequal noise variances incurred in different bands. As a result, a band with small variance does not necessarily mean poor image quality. It may have a high SNR compared to other bands with large variances but low SNR’s.

In order to develop a maximum noise fraction (MNF) transformation based on maximization of SNR,so that the transformed principal components are ranked by SNR rather than variance as used in a PCA. This MNF using a two-stage process comprised of a noise-whitening process and a PCA to achieve what the MNF transform does. This new derived transform is referred to as a noise adjusted principal components (NAPC) transform.

As a powerful multilinear algebra model, parallel factor analysis is one of several decomposition methods for multiway data. PARAFAC decomposition has the distinguishing unique- ness characteristics,low-rank PARAFAC decomposition can be unique for rank values higher than one. Based on this property,PARAFAC decomposition, which needs to estimate only one rank, was proposed to denoise HSI, and the experimental results showed its promising performance in the reduction of SI white noise. Both the uniqueness and the one- rank properties help its popular applications in many fields.

III. SI Noise Reduction Method

Three effective denoising methods are introduced in the following sections.

A. Hyne Method

Hyperspectral sensors measure the radiance from the observed scene in many spectral bands very close in wavelengths; thus, the signal X is generally characterized as having strong spectral correlation [8]. According to [8] noise sources are commonly assumed to be independent from one another.

B. Multidimensional Wiener Filtering

As an extension of the Wiener filter to the multidimensional case based on TUCKER3 tensor decomposition [14], the MWF method had been proved to be effective for the denoising of WGN[12], [13] using multilinear algebra tools. At first signal and noise are separated. The Wiener Filter used to minimize the mean squared error by taking the estimation for the target image.

Denoising Based On Parafac Decomposition

The PARAFAC model and the CANDECOMP model developed respectively. The CANDECOMP /PARAFAC model, referred to as the CP model has recently been applied to food industry, array processing . PARAFAC decomposition of a tensor containing data received on an array of sensors yields strong identifiability results. Identifiability results depend firstly on a relationship between the rank, in the sense of PARAFAC decomposition, of the data tensor. In particular, nonnegative tensor factorization is used in multiway blind source separation, multidimensional data analysis, and sparse signal/image representations. Fixed point optimization algorithm and more specifically fixed-point alternating least squares can be used to achieve such a decomposition.

The PARAFAC decomposition can reduce the SI white noise with the lowest loss of signal. If HSIs are contaminated by non-white SI noise, the noise will be colored, i.e., the noise variance is different from band to band. Since the denoising by PARAFAC decomposition is based on skipping smaller terms,where perhaps some SD noise components exist, PARAFAC decomposition has the effect of the reduction of a small portion of SD noise.

IV. Reduction Of Both Si And Sd Noise

Denoising has been a problem for years, particularly to improve classification or target detection. In practice, although the average noise level is so low that it is not visible in the acquired HSI. There are several approaches to filter multidimensional data. A common one is to consider the modes of the tensor as separable to enable classical 1-D or 2-D methods. Another interesting approach uses a hybrid filtering relying on the decorrelation of channels. However, they could lead to a loss of interdimension relationships. In this paper, we propose a tensor method, the PARAFAC model, which permits to process the tensor data as a whole entity. For comparison, another tensor method, Tucker3 model, is introduced.

The SD photonic noise contribution has become as dominant as the SI electronic noise in HSI data. Hence, preprocessing and analysis methods must be revised or designed to take into account the SD noise. Since the HYNE and MWF methods and PARAFAC decomposition were proved to be effective methods for denoising HSIs .we propose three two-step methods to first delete SI noise from HSI data by the HYNE and MWF methods or PARAFAC decomposition and then reduce the SD components by PARAFAC decomposition method.

A. Si Noise Reduction

Generally assumed as zero-mean WGN whose covariance matrix is a scalar matrix with all its main diagonal entries being equal to the noise variance. Hence HYNE and MWF methods can be used to denoise the WGN. The PARAFAC decomposition can also denoise the WGN by selecting an appropriate rank. However in some HSIs, the SI noise was colored i.e., non-white. In this case the HYNE method and PARAFAC decomposition can also effectively reduce the colored SI noise. For the PARAFAC decomposition to remove the colored SI noise.

The results of noise reduction by the HYNE method and MWF method in [12] and [13], and PARAFAC decomposition influence on the signal by the filtering processes is very little and can be ignored. Therefore in this paper we assume that the statistical properties of both the signal and the remaining SD noise after the SI noise reduction are relatively

B. Sd Noise Reduction

we can neglect the remaining SI components after the denoising SD. According to the analysis we know that the selection of the rank is the key factor to remove SD noise by PARAFAC decomposition.

C. Reducing Both SD And White Or Colored SI Noise

The common filtering methods for HSIs are based on the data vectorization or matricization while ignoring the related information between image planes, there are new approaches considering multidimensional data as whole entities, for example, multidimensional Wiener filtering (MWF) based on Tucker3 tensor decomposition. However if HSIs are not disturbed by white noise, MWF cannot effectively remove the nonwhite noise and obtain the expected signal. To reduce nonwhite noise from HSIs, a new method is proposed in this letter.

Relying on Tucker3 decomposition, an extension of the Wiener filter to a multidimensional (MWF) case was proposed. This MWF has been shown to be more efficient than classical channel-by-channel Wiener filtering or other multidimensional filtering methods to denoise data sets with additive white noise. However, this filtering method does not consider the cases with nonwhite noise. Thus, we propose a prewhitening approach for HSIs which could change the nonwhite noise to a white one, then MWF can be used to filter the prewhitened HSIs. We compare the denoising performance of our proposed method, prewhitening and MWF, named as PMWF, to MWF, principal component analysis (PCA),

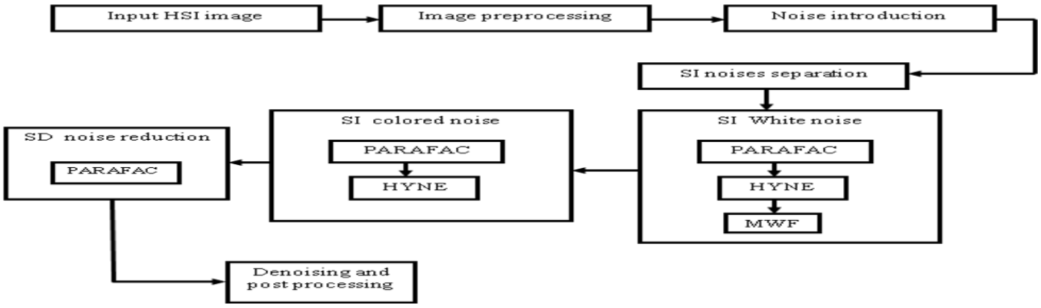


Fig. 1 Proposed algorithms for the reduction of both SI an SD noise

minimum noise fraction (MNF), and two hybrid filters which consist of a 2-D Wiener filtering on the spectral bands reconstructed and decorrelated by PCA or MNF. The results show that provides better performance in the case of reducing nonwhite noise in HSI

V. Experiments

One of the most important applications of HSI is target detection, which can be viewed as a binary classification problem where pixels are labeled as target or background based on their spectral characteristics. Target detection enables efficient surveillance and terrain characterization over wide areas because it seeks to locate pixels containing a target material of known spectral composition and is desired to detect the presence of a signal of interest embedded in noise.

Therefore in this paper, we focus on the improvement of target detection using the coherence/cosine estimator (ACE) which is largely applied to HSI data. The random noise is generated with a variance depending on the value of the useful signal and added into the signal as to create the simulated HSI data.

A.Result on Simulated Data

(a)

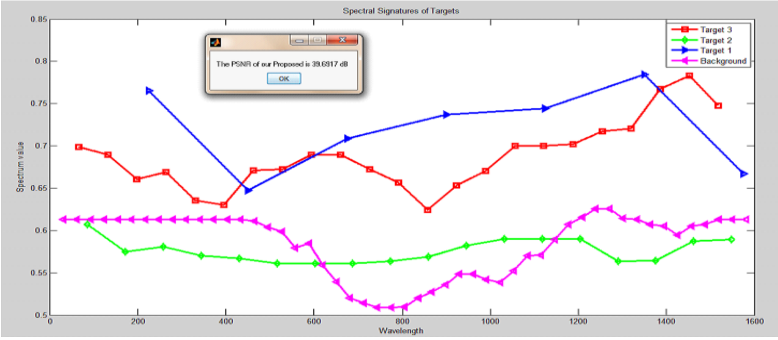
Fig. 3. (a) Simulated HSI without noise with target 1,2,3.b) spectral content of targets.

To assess the denoising performance, we have compared our proposed HYNE-PARAFAC, MWF-PARAFAC, and PARAFACSI–PARAFACSD methods against other considered methods in this paper. The optimal SI and SD ranks of PARAFAC decomposition in the PARAFACSI – PARAFACSD method are selected. The optimal ranks of PARAFAC decomposition in HENE-PARAFAC and MWF-PARAFAC methods are chosen according to the criterion of SD rank estimation. For PARAFAC decomposition, the optimal rank is selected according to the criterion of white SI rank estimation. The three ranks of MWF and MWF-PARAFAC methods and the PMWF method, are selected by minimizing the AIC criterion.

The ACE target detection results of simulated HSI denoised by the considered methods and the variance of the residual noise.Probability of Detection: The Pd of ACE target detection for simulated HSI denoised by the considered methods in this paper, and the Pd values are obtained when the probability of false alarm (Pfa) is $10{-}3$.

The signal becomes weaker, and this correlation is further decreased by the stronger noise in HSIs. Since the HYNE method seeks to exploit the spectral correlation of the signal, the effect of noise reduction by HYNE- based methods is decreased by the weak correlation among bands of the signal, and the target detection of HSIs denoised by HYNE-based methods is affected correspondingly.

PSNR of Denoised HSIs: To assess the noise reduction performance of different methods, the PSNR of denoised HSIs The improvement of the PSNR of simulated HSIs denoised by the proposed methods can be seen clearly.



(b)

The proposed PARAFACSI –PARAFACSD method is robust to SNR and different proportions of SD to white SI noise in the simulated HSI and the above assumption of the statistical properties of both the signal and the remaining SD noise being relatively constant after the SI noise reduction can be done in the practice. The HYDICE HSI with spectral bands is considered in this experiment. Several wave- lengths were removed regarding the low-signal/high-noise bands and water vapor absorption bands. It can be represented as a 3-D data cube, Six targets are added into the a image, and each row of targets has the same target spectral signature which is taken from the image itself.

To estimate the results obtained by the PARAFACSI –PARAFACSD method, we can only resort to other indirect ways. Therefore, the receiver operating characteristic (ROC) curves of ACE target detection that only the removed noise. Therefore, the removed noise variance is calculated. The second real-world HYDICE HSI used in this experiment there already exist six targets in the image, and the target spectral signatures are illustrated.

Since the Pd values of ACE target detection of the denoised images by the HYNE-PARAFAC and PARAFACSI – PARAFACSD methods are similar. It can be concluded that the PARAFACSI –PARAFACSD method still has some potential prospective in the reduction of both SD and colored SI noise. The MWF method can only deal with white noise; therefore, the results of target detection of the denoised images by both MWF and MWF-PARAFAC methods are inferior to those by PARAFAC decomposition when the SI noise is colored. The denoising performance of the PMWF, noise-adjusted PCA, and MNF methods are not ideal because they are not designed for SD noise reduction.

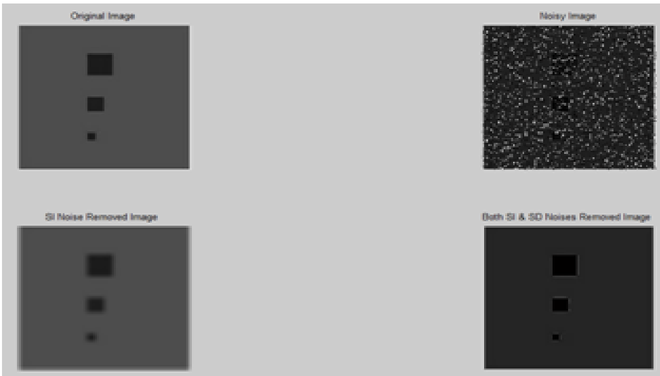


Fig. 4. Noise reduction steps

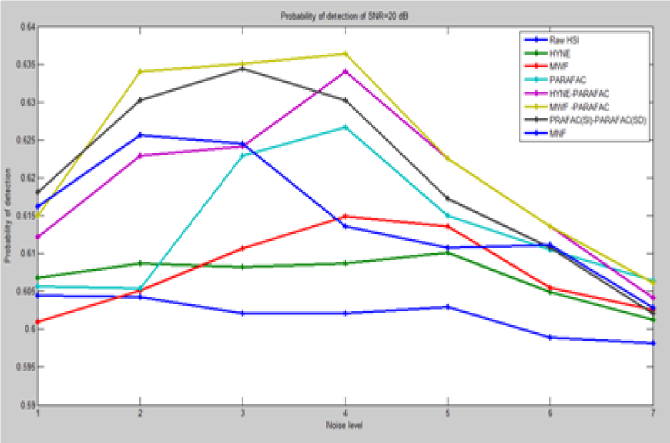


Fig. 5. Probablity of detection using different method

VI. Conclusion

In this paper, the problem of noise estimation in HSIs acquired by new-generation sensors has been investigated. The sensors, electronic noise cannot be considered dominant with respect to photon noise, which depends on the signal values.

Hyperspectral target detection is a multidisciplinary problem that draws results from different scientific and engineering areas. First, we assumed that one of the two noise sources (SD and SI) is dominant with respect to the other, and then, we considered the case in which the two noise contributions are of the same order .

The PARAFAC model is first introduced to denoising and proved to be a good method to reduce additive WGN from HSI by exploiting its decomposition uniqueness and its single rank character. Its optimal rank is calculated based on that the covariance matrix of the n-mode unfolding matrix of the removed noise should be approach to a scalar matrix. Numerical results show that the PARAFAC model performs much better than other considered methods as a denoising procedure for the classification.

First, PARAFAC decomposition and HYNE and MWF methods can be applied to remove the white SI noise, or PARAFAC decomposition and the HYNE method can be used to delete the colored SI noise. Then, to reduce the residual SD components, PARAFAC decomposition is applied to the denoised HSI by the previous step. PARAFAC decompositions must be conducted at the appropriate rank, which can be estimated according to the different statistical properties of SI and SD noise, respectively.

A two-stage process composed of a noise prewhitening

procedure and an MWF process. We focus on its ability as a preprocessing algorithm that improves SNRout, results applied to real-world HYDICE data. The comparison to MWF, PCA, PCA–Wiener, MNF, and MNF–Wiener permits to appreciate the denoising efficiency of our method in the application of target classification in noisy HYDICE HSI.

The MWF and PARAFAC were proposed to process the HSI as a whole entity, but this may remove the small targets in an HSI in the denoising process. Distinguishing from MWF and PARAFAC, MWPT-MWF firstly transforms the HSI into different wavelet packet sets, also called components and then filters each component as a whole entity. As the small targets are separated from the large ones, the former can be well preserved in the denoising process.

From the analysis and the comparative study against other similar methods in the experiments, it can be concluded that PARAFACSI PARAFACSD and HYNE-PARAFAC methods can effectively reduce both SD and white or colored SI noise from HSIs. It is also necessary to take into account the noise signal-dependence hypothesis when dealing with HYDICE data. If HSIs are distorted by both SD and white SI noise, the MWF-PARAFAC method is also a considerable choice for the noise reduction

The derivation of adaptive algorithms to track the PARAFAC decomposition of tensors of any order for which only one mode is growing can be done in the same way as for the three-way case

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