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A COMPARATIVE STUDY ON NOISE ESTIMATION FOR HYPERSPECTRAL IMAGERY

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ABSTRACT

In the traditional signal model, signal is assumed to be deterministic, and noise is assumed to be random, additive and uncorrelated to the signal component. A hyperspectral image has high spatial and spectral correlation, and a pixel can be well predicted using its spatial and/or spectral neighbors; any prediction error can be considered from noise. Using this concept, several algorithms have been developed for noise estimation for hyperspectral images. However, these algorithms have not been rigorously analyzed with a unified scheme. In this paper, we conduct a comparative study for these algorithms using real images with different land cover types. Based on experimental results, instructive guidance is concluded for their practical applications.

Index Terms — Hyperspectral imagey, noise estimation, multiple linear regression.

1. INTRODUCTION

The development of high spectral resolution image sensors improves the capability of monitoring the Earth system and human activity on the Earth. Due to the fact that hyperspectral imaging spectrometers adopt very narrow band intervals, energy acquired in each band is not enough to generate high Signal-to-Noise Ratio (SNR). Spectral features in hyperspectral imagery (HSI) can be easily confused as a result of noise influence. Only when the level of noise is quantitatively lower than the depth of spectral absorption, the spectral feature can be recognized. In HSI processing, the performance of many algorithms commonly is affected by noise, such as classification, spectral unmixing, and target detection, because most of these algorithms assume a signal/noise model in their formulas. Hence, accurate noise estimation can be beneficial for them in HSI information exploitation.

The noise in HSI usually belongs to one of two types: random noise and periodic noise. Periodic noise has fixed pattern and can be removed using suitable procedures. However, random noise cannot be predicted in advance and also cannot be removed completely [1-3]. Therefore, random noise mainly is concerned in information exploitation. The random noise in HSI is generally assumed to be additive and uncorrelated with the signal. The signal model described here can be expressed as

$$x_{i,j,k} = s_{i,j,k} + n_{i,j,k} \tag{1}$$

where $x_{i,j,k}$ is the image Digital Number (DN) at coordinate (i,j) in band k, $s_{i,j,k}$ and $n_{i,j,k}$ are signal and noise components of $x_{i,j,k}$, respectively. Here, it is assumed that signal is deterministic and random noise is additive and uncorrelated to signal.

A hyperspectral image has high spatial and spectral correlation, and a pixel can be well predicted using its spatial and/or spectral neighbors; any prediction error can be considered from noise [4]. Using this concept, several algorithms have been developed for hyperspectral noise estimation. In this paper, we investigate their performance when image contents are changed. Note that we focus on the estimation of noise Standard Deviation (SD) in each band.

2. NOISE ESTIMATION ALGRITHMS

One simple noise estimation algorithm, referred to as the Homogeneous Area method (HA), uses the mean of standard deviations of several visually homogeneous regions as noise estimate [5]. Curran and Dungan [6] developed the Geo-Statistical method (GS), where some narrow homogeneous strips are selected to estimate the noise. However, in these two methods, the homogeneous regions within an image need to be manually selected, but homogeneous regions can be difficult to identify in most images.

To improve the performance, several algorithms are developed to more reliably estimate noise in HSI with less human intervention, such as Local Means and Local Standard Deviations method (LMLSD) [7], Spectral and Spatial De-Correlation method (SSDC) [4], Homogeneous Regions Division and Spectral De-Correlation method (HRDSDC) [8], and Residual-scaled Local Standard Deviation method (RLSD) [9]. A brief overview of these methods is summarized in Table I. Similarly, they have three major steps: image spatial partition, Local Standard Deviation (LSD) estimation of noise, and global noise estimation based on local information.

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A. LMLSD

In this method, an entire image is uniformly divided into non-overlapping small blocks with $w \times w$ pixels. It is assumed that each block is mainly homogeneous. Then, the local mean of a block is related to the signal, and the deviation from the local mean is due to noise. Thus, the LSD of each block is estimated, which is considered as noise standard deviation of the block. Within the range of the minimum and maximum value of these standard deviations, a number of bins of equal width are delineated. The number of blocks falling into each bin is counted, and the bin with the largest number of blocks represents the noise standard deviation of the entire image.

B. SSDC

In this method, the image also is uniformly divided into non-overlapping small blocks with $w \times w$ pixels. The pixel value at (i, j) in band k can be predicted by its spatial and spectral neighbors and the residual $r_{i,j,k}$ is calculated as

$$r_{i,j,k} = x_{i,j,k} - \hat{x}_{i,j,k} \qquad (2)$$

where $\hat{x}_{i,j,k}$ is the linear predicted value of $x_{i,j,k}$, and is computed as follows

$$\hat{x}_{i,j,k} = a + bx_{i,j,k-1} + cx_{i,j,k+1} + dx_{p,k} \qquad (3)$$

where a, b, c, and d are the coefficients computed using Multiple Linear Regression (MLR). The LSD of all the residuals in a block is computed using

$$LSD = \left[\frac{1}{w^2 - 4} \sum_{i=1}^{w} \sum_{j=1}^{w} r_{i,j,k}^2 \right]^{1/2} \qquad (4)$$

The mean value of these standard deviations is used as the noise estimate for the entire image. Note that Eqs. (2) and (3) use two spectral neighbors and one spatial neighbor for MLR. If more neighbors of $x_{i,j,k}$ are also used, then more MLR coefficients are to be determined, similarly with the Least Squares (LS) method.

C. HRDSDC

In HRDSDC, an image segmentation algorithm based on the general internal regularity of earth objects in natural scene is applied first to partition the image into spectrally homogeneous regions. Then, MLR is applied to each homogeneous region to calculate residuals using spectral neighbors. The mean value of residual standard deviations in local regions is used as the global noise estimate.

D. RLSD

RLSD can be considered an effective improvement of LMLSD. In each block, instead of using LSD as local noise estimate, the residuals from the MLR in the spectral domain are used for local noise estimation. Then the histogram of LSD is computed, and the one with the maximum counts is the noise standard deviation for the entire image. RLSD can produce more accurate estimation than LMLSD.

TABLE I
SUMMARY OF NOISE ESTIMATION ALGORITHMS

Algorithm	Nature	Assumption	Key procedure	Information use
HA	Supervised	Image contains homogeneous area in each object	SD calcula-tion	Spatial
GS	Supervised	Image contains homogeneous area in each object	Semi-variance function	Spatial
LMLSD	Near-automated	Image mainly contains homogeneous blocks	Block size, LSD statistics	Spatial
SSDC	Near-automated	High spectral and spatial correlations	Block size, MLR	Spatial Spectral
HRDSDC	Near-automated	Object internal regularity, high spectral correlation	Segmenta-tion, MLR	Spatial Spectral
RLSD	Near-automated	High spectral correlation	Block size, MLR, LSD statistics	Spatial Spectral

3. EXPERIMENT

A. Data sets

To assess the performance of aforementioned algorithms, eight real AVIRIS radiance images in Fig. 1 with very different spatial features are used in the experiment. All these images have the same size: 500×500 pixels and 221 bands. More detailed descriptions are shown in Table II.

TABLE II
DETAILED DESCRIPTION OF AVIRIS IMAGES SHOWN IN FIG. 1.

Fig. 1	Spatial Resolution	Acquired site	Image description
(a)	20m	Cuprite	Homogeneous minerals
(b)	20m	Lunar Lake	Homogeneous gobi
(c)	20m	Jasper Ridge	Heterogeneous city
(d)			Homogeneous vegetation
(e)	3.4m	Low Altitude	Heterogeneous city
(f)			Homogeneous farmland
(g)	20m	Moffett Field	Heterogeneous city
(h)			Homogeneous water

The images in Fig. 1 were acquired from 07/1996 to 06/1997. The sensor parameters of AVIRIS were changed

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little and noise level may be similar in these images. In particular, Fig. 1(c) and 1(d), Fig. 1(e) and 1(f), Fig. 1(g) and 1(h) are cut from the same image, respectively. Therefore, their noise feature should be the same. The comparative analysis of these three pairs will test the stability of noise estimation.

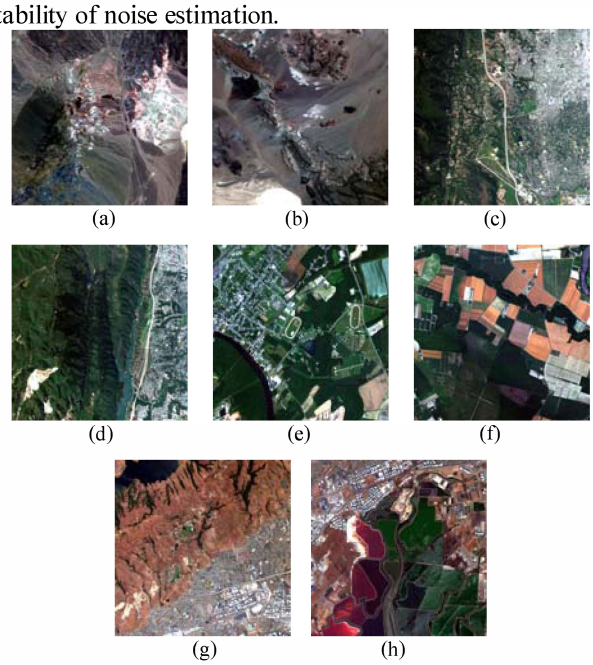

Fig. 1 AVIRIS radiance images used for noise estimation.

B. Parameter selection

As summarized in Table I, SSDC and HRDSDC adopt the mean value of LSDs of small blocks or local regions after MLR. On the contrary, in LMLSD and RLSD, noise is estimated through the estimation of LSD histogram, so we use the parameters in [7] to find appropriate bins. In LMLSD and RLSD, bins are set in the range between the minimum LSD of all blocks and 1.2 times the average LSD of all blocks, and 150 bins are used for noise estimation.

The block size is the most important parameter for LMLSD, SSDC, and RLSD. In the experiment, the blocks of size 4×4, 5×5, 6×6, 7×7, and 8×8 are tested. For LMLSD, since it is assumed that an image mainly is composed of many homogeneous small blocks, 4×4 is an appropriate choice in our experiment. It seems that a smaller block size is also beneficial for SSDC and RLSD. However, when the block size is 4×4 or 5×5, some homogeneous blocks in most experimental data have similar DN value in certain bands; as a consequence, it makes the inverse matrix calculation in LS infeasible. Thus, the block of size 6×6 is adopted for SSDC and RLSD. As for the HRDSDC, it employs more advanced image segmentation, whose step and related parameters are the same as in [8].

C. Noise estimation with different land cover types

Fig. 2 shows the noise estimates from LMLSD for the eight image scenes in Fig. 1. They are varied along with land cover types, which is not reasonable. It may be because that most image blocks do not meet the homogeneous assumption made by LMLSD, in particular, when an image is simply uniformly partitioned. Only when the primary land cover type is water, the image can be homogeneous enough to find adequately effective blocks. Experimental results show that noise estimates from SSDC is better than LMLSD. HRDSDC, considered as modified SSDC using image segmentation as spatial partition, generated also better result as shown in Fig. 3.

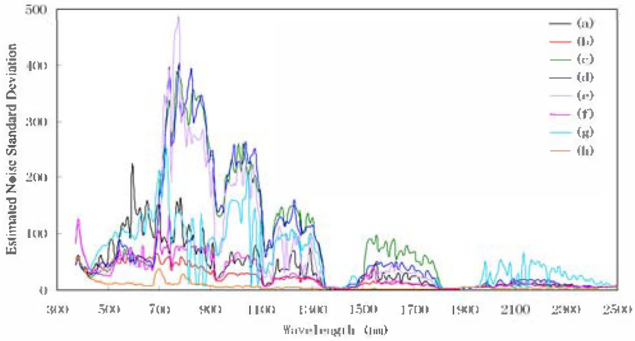

Fig. 2 Noise estimation results of Fig. 1 using LMLSD.

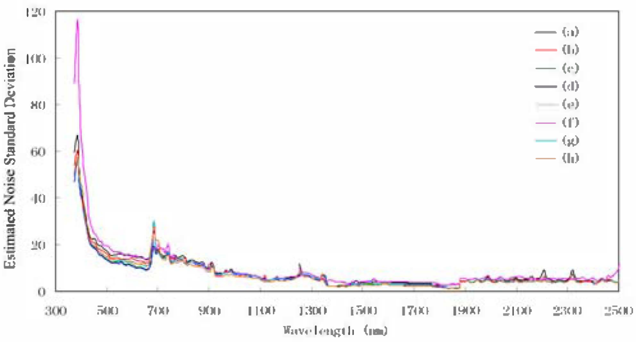

Fig. 3 Noise estimation results of Fig. 1 using HRDSDC.

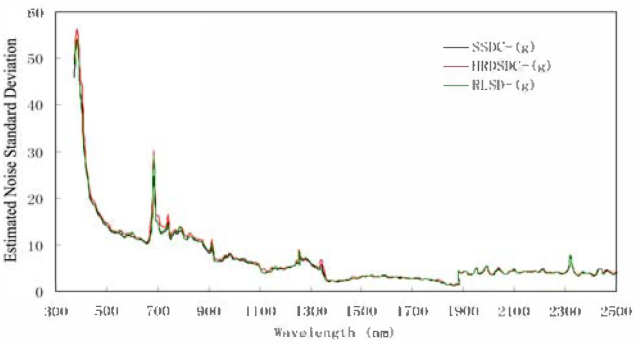

Fig. 4 Noise curves in estimated noise image of Fig.1(g) using SSDC, HRDSDC, and RLSD.

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Noise estimates shown in Figs. 3 and 4 using SSDC, HRDSDC, and RLSD are better results in terms of that noise estimates are less sensitive to image contents. Though these algorithms consider spectral and spatial information in different ways, the noise estimated results shown in Fig. 4 are very similar. The noise estimate for Fig. 1(e) and 1(f) with 3.4m spatial resolution is larger than others with 20m spatial resolution.

D. Noise estimation for images covered by water

Areas covered by water always are very homogeneous. However, spectrum of water from near infrared spectroscopy to shortwave infrared spectroscopy is nearly equal to zero. Therefore, many methods may get lower noise estimation result than the actual value (e.g., results shown in Fig. 5 by SSDC and Fig. 6 by HRDSDC). It is because that their procedure of mean value calculation of LSDs cannot avoid the influence of very low radiance, and not suitable for noise estimation of images mainly covered by water. However, RLSD produced better results as shown in Fig. 7, which may be because that it uses the LSD with the maximum occurrence as the noise estimate for the image.

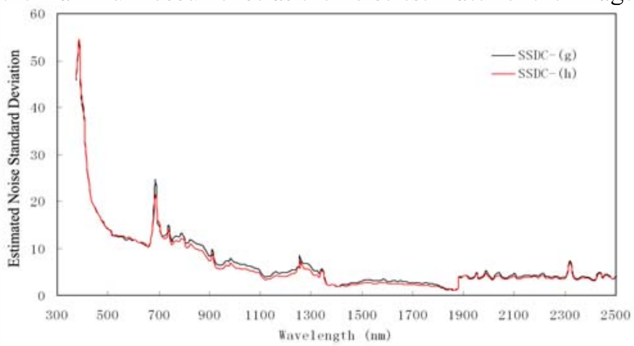

Fig. 5 Noise estimation results of Fig. 1 (g) and (h) using SSDC.

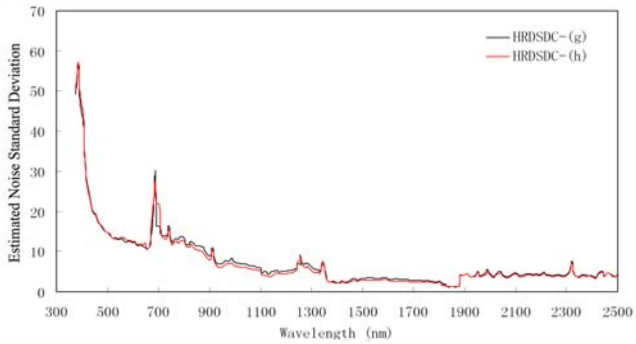

Fig. 6 Noise estimation results of Fig. 1 (g) and (h) using HRDSDC.

4. CONCLUSION

Several noise estimation algorithms for HSIs are analyzed in this paper. Parameters of these algorithms are discussed. Qualitative comparisons of these algorithms are provided using real data with different land cover types. It is found out that: 1) The simply uniform spatial partition with small block size, say, 6×6, can perform as well as more sophisticated image segmentation; 2) the residual of MLR is an effective feature for noise estimation; and 3) the histogram of LSD is more appropriate than the simple average of LSD for global noise estimation.

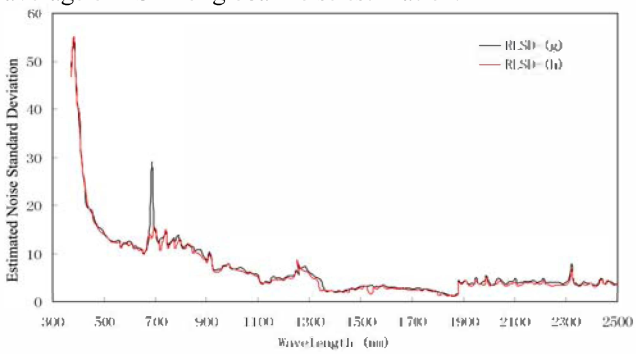

Fig. 7 Noise estimation results of Fig. 1 (g) and (h) using RLSD.

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