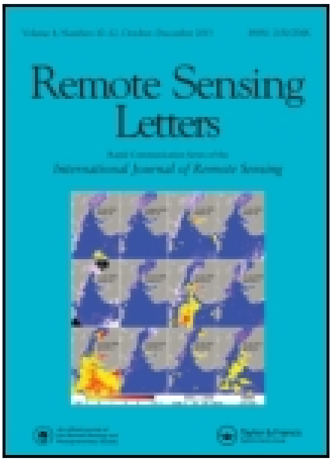

Remote Sensing Letters
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/trsl20

A generally applicable noise-estimating method for remote sensing images

Bangyong Qin[ab], Bo Hong[a], Zhi Zhang[a], Xiaofeng Yang[a] & Ziwei Li[a]

[a] State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China

[b] College of Resources and Environment, University of Chinese Academy of Sciences, Beijing, China

Published online: 06 Jun 2014.

To cite this article: Bangyong Qin, Bo Hong, Zhi Zhang, Xiaofeng Yang & Ziwei Li (2014) A generally applicable noise-estimating method for remote sensing images, Remote Sensing Letters, 5:5, 481-490, DOI: 10.1080/2150704X.2014.923126

To link to this article: http://dx.doi.org/10.1080/2150704X.2014.923126

Remote Sensing Letters, 2014
Vol. 5, No. 5, 481–490, http://dx.doi.org/10.1080/2150704X.2014.923126

A generally applicable noise-estimating method for remote sensing images

Bangyong Qin[a,b]*, Bo Hong[a], Zhi Zhang[a], Xiaofeng Yang[a], and Ziwei Li[a]

[a]*State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China;* [b]*College of Resources and Environment, University of Chinese Academy of Sciences, Beijing, China*

(*Received 17 February 2014; accepted 6 May 2014*)

Local mean and local standard deviations (LMLSD), which is one of the most widely used methods for estimating noise in remote sensing images, is suitable only for the images with many homogeneous regions. For those composed of heterogeneous features and textures, it may cause overestimation of noise. Edge-extracted local standard deviations (EELSD) method performs better than LMLSD in most instances, but it still cannot work out the accurate noise estimation in most heterogeneous images. Spectral and spatial de-correlation (SSDC) is an effective noise-estimation method for hyperspectral images. However, it cannot be applied to single-band or multispectral images because of the use of pixel spectral information in the calculation process. In this article, a new noise-estimating method for remote sensing images, which is based on the principle of LMLSD and has made improvements in three aspects, is proposed. The new method has been tested with several Airborne Visible Infrared Imaging Spectrometer images with different degrees of uniformity. Compared with LMLSD and EELSD, the results of the improved method are more accurate, stable, and applicable in terms of complex land cover types. Furthermore, in contrast to SSDC, this method is suitable not only for hyperspectral images but also for single-band and multispectral images.

1. Introduction

Quality evaluation of remote sensing images is a key step in image processing, which is also a prerequisite for the production and application of remote sensing data (Wang and Bovik 2002; Wang, Bovik, and Lu 2002; Garzelli and Nencini 2009). Among several evaluation indicators, signal-to-noise ratio (SNR) is one of the most extensively used indices (Chen et al. 2012). SNR reflects the relative size between the average signal and noise levels in images and includes important guiding significance for the application of remote sensing data (Gao, Zhang, Zhang, et al. 2007; Zhu et al. 2012).

In optical remote sensing systems, image noise includes not only periodic noise (system noise) that can be eliminated by frequency-domain transform filtering but also random noise that cannot be removed completely (Al-amri, Kalyankar, and Khamitkar 2010; Gao et al. 2013). In this article, we mainly focus on the latter one, which is generally additive noise and independent of the image signal (Corner, Narayanan, and Reichenbach 2003).

Noise assessment methods for remote sensing images mainly include homogeneous area (HA) (Van der Meer and De Jong 2001), geo-statistical (GS) (Curran and Dungan

*Corresponding author. Email: bangyong_whu@163.com

1989), local means and local standard deviations (LMLSD) (Gao 1993), spectral and spatial de-correlation (SSDC) method (Roger and Arnold 1996) and other improved methods based on these already-existing ones. The HA method needs selecting more than four homogeneous regions in the image manually for noise estimation, and thus, it cannot be achieved with automatic calculation. The GS method requires picking up several homogeneous narrow strips from images; the result may be affected by the uniformity of the selected strips (Chen and Xue 2000), and this method is not easy to be automated (Gao, Zhang, Zhang, et al. 2007).

The LMLSD method is relatively simple and can be used for automatic calculation, it is widely used in various types of remote sensing images for noise estimation (Gao, Zhang, Zhang, et al. 2007). However, this method is seriously affected by land cover types and often causes overestimation of noise when applied to an image containing complex land types and texture features (Gao et al. 2013). Gao, Zhang, Zhang, et al. (2007) have proposed an improved method based on LMLSD, called edge-extracted local standard deviations (EELSD). EELSD can reduce the effect of feature complexity to some extent; yet, it still cannot assess the noise value accurately in most heterogeneous images.

SSDC makes use of the high within-band (spatial) correlations and between-band (spectral) correlations between pixels to estimate the noise in hyperspectral images. It works well with heterogeneous images and can be calculated automatically; SSDC is considered as an effective and stable method for hyperspectral images (Chen and Xue 2000; Gao, Zhang, Zhang, et al. 2007). Some scholars have proposed analogous approaches, such as homogeneous regions division and spectral de-correlation method (Gao et al. 2008) and residual-scaled local standard deviation method (Gao, Zhang, Wen, et al. 2007). However, since these methods need spectral information for noise estimation, they are not suitable for single-band or multi-band remote sensing images.

In this article, we proposed a new noise-estimation method, named homogeneous region division and residuals statistics (HRDRS). This method is reliant on the strong spatial correlations between neighbouring pixels and is independent of spectral information; therefore, it can be applied to single-band and multispectral remote sensing images as well as hyperspectral images. Unlike LMLSD, this method can work well not only with images having homogeneous features but also with the ones containing complex land cover types and texture features.

2. Methodology

In remote sensing images, there are strong spatial correlations between adjacent pixels (Roger and Arnold 1996; Gao et al. 2013). Both the LMLSD and EELSD methods use spatial correlation to estimate the image noise. In LMLSD, the image is divided into many neighbouring small blocks with $n \times n$ pixels in size, and the standard deviations (SD) of each block is calculated. Then within the range of the minimum and maximum values of these SDs, multiple bins of equal width are defined. The number of blocks with SDs falling into each bin is counted, and the bin with the most blocks is viewed as the best estimation bin. The mean SD in this bin is considered to be equal to the optimal estimated value of the noise in the image. The legitimacy of this method relies on the assumption that the images are composed of many homogeneous blocks along with a few heterogeneous blocks. For the images containing complex land cover types and rich texture, the bin with the maximum number of blocks may be composed of heterogeneous blocks rather than homogeneous blocks; in this case, the LMLSD method would cause overestimation of image noise (Gao, Zhang, Zhang, et al. 2007; Gao et al. 2013).

In EELSD, the Canny (1986) algorithm is employed to detect the edges of land objects in images, and then the noise level of images is estimated with remaining blocks after removing the blocks containing edges. This technique decreases the effects of inhomogeneous blocks to some extent, but the result is still erroneous if the image contains rich texture information.

The new method proposed in here (HRDRS) makes three improvements on the basis of LMLSD and EELSD. Firstly, to reduce the effects of heterogeneous regions, image segmentation algorithm is used for homogeneous region extraction in images. Secondly, a plane fitting algorithm is applied to simulate the image signals in each block, and the residual fitting errors are used to calculate the amount of noise, which can decrease the impact of texture features on noise estimation. Finally, a new approach for searching optimal noise-estimation interval is proposed, which can avoid the negative effects of multipeak distribution of block SDs on the noise-estimation results. The flow chart of HRDRS is shown in Figure 1.

2.1. Edge detection

Noise-estimation methods based on the local SD require finding homogeneous regions from which to calculate the level of noise (Gao 1993). The blocks containing object edges are covered by different land types and could not be homogeneous blocks; therefore, these blocks should be detected and eliminated before calculating the SDs of each blocks. There are many

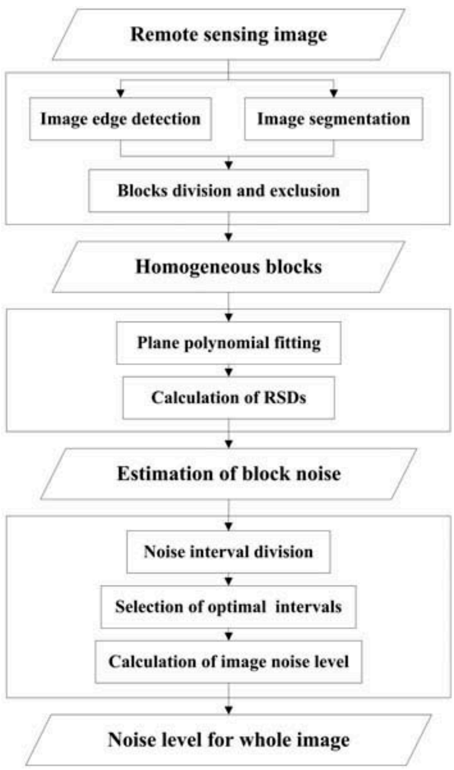

Figure 1. Flow chart of the proposed HRDRS method.

edge detection algorithms. According to Gao, Zhang, Zhang, et al. (2007), Canny algorithm performed best among them; therefore, we use Canny algorithm for edge detection in this article.

2.2. Homogeneous regions detection

Remote sensing images are mostly composed of objects and background. Objects are relatively complex, while background is usually homogeneous. To reduce the effects of heterogeneous regions, we use the Otsu (1979) adaptive threshold method to extract the background regions for image noise estimation in this article.

The Otsu method is a classical image segmentation algorithm based on optimal threshold and is extensively employed in image processing (Sezgin and Sankur 2004; Lang et al. 2008). The basic principle of this method is as follows (Otsu 1979):

Firstly, use a certain grey value as a threshold to divide the image into two parts (classes); when the between-class variance of the two parts is largest, the grey value is considered the optimum threshold.

Secondly, calculate the within-class variances of the two parts respectively, the class with smaller variance is considered the background of the image, and the other class is regarded as the target region. Only the background regions, which are supposed to be homogeneous, are used in the calculation of the level of image noise.

2.3. Fitting residual calculation of blocks

After eliminating the blocks containing edges and inhomogeneous regions, the residual blocks are still not completely homogeneous because of the presence of texture features. In LMLSD and EELSD, block SDs are used to calculate the level of noise in each block. For those blocks containing complex texture features, the estimated results will be higher than the actual noise level.

In this article, we adopted a plane polynomial to fit the grey values of each block and used the residual fitting errors to calculate the amount of noise in each block. Comparing to the SDs, using the residual fitting errors to calculate the noise level of each block could reduce the impact of texture features and produce more accurate results. The calculation process is as follows.

Firstly, the remaining blocks, after eliminating the blocks containing edges and inhomogeneous regions, are separately fitted with the polynomial described in Equation (1).

$$f'(i,j) = \mathrm{a} + \mathrm{b}i + \mathrm{c}j \tag{1}$$

where i and j are the block row and column numbers, $f'(i,j)$ is the fitted value at position (i,j) and a, b and c are the fitting coefficients.

Then the residual fitting errors are calculated as follows.

$$\Delta f(i,j) = f'(i,j) - f(i,j) \tag{2}$$

Where $f(i,j)$ is the pixel value at position (i,j), $\Delta f(i,j)$ is the residual fitting error.

Finally, the SD of the residual fitting errors is considered to be the estimate of the amount of noise in each block. The SD is calculated as follows.

$$\sigma = \sqrt{\left[\sum_{i=1}^{n}\sum_{j=1}^{n}(\Delta f(i,j))^2\right]/(n^2-1)} \tag{3}$$

where n is the width and height of each block, and σ is the residual standard deviation (RSD) of each block.

2.4. Selection of the best estimation interval

Due to the presence of non-uniform blocks, it is necessary to select effective blocks to participate in the noise estimation of the entire image. In this method, the minimum value and the mean value of blocks RSDs obtained in the previous step are calculated. Then, the range between the minimum and 1.2 times the mean of RSDs are divided into 150 equally spaced intervals. The number of blocks falling into each interval is counted to form a frequency curve with 150 points. The frequency curve is searched from left to right. The first point found to have the maximum value in the range stretching 15 points to its left and right is taken to be the first valid peak of the curve. Its corresponding interval will be viewed as the best estimating interval. The mean of the RSDs of blocks falling into the best interval is calculated as the noise estimation of the whole image.

3. Image data

To validate the accuracy of the HRDRS method and its applicability to complex land types, four Airborne Visible Infrared Imaging Spectrometer (AVIRIS) images were used for noise estimation. AVIRIS, developed by the NASA Jet Propulsion Laboratory (JPL/NASA), has 224 contiguous spectral bands with wavelengths from 400 to 2500 nm. Its spatial resolution is 20 m when imaging at a height of 20 km, and the spectral resolution is approximately equal to 10 nm (Green et al. 1998).

The four images used in this study were obtained from the same flight experiment, which was conducted on 20 June 1997. The location was in the Moffett Field region, California, USA. For ease of calculation, only 100 bands (414.29–1333.15 nm) were used for noise evaluation, and the image size was 500 × 500 pixels. Detailed information regarding the images is shown in Table 1.

As shown in Figure 2, the land cover types of the four images have distinct differences, and their degree of uniformity is not the same. Image (*a*) mainly consists of water and farmland and is relatively uniform; image (*b*) is mainly composed of mountains and cities and has weak degree of uniformity; image (*c*) contains large area of water and has higher degree of uniformity, while image (*d*) is predominantly composed of cities, with a small amount of homogeneous water and has the lowest degree of uniformity.

Table 1. Detailed information of AVIRIS images.

Image	Size (m)	Resolution (m)	Land cover type	Uniformity degree
(*a*)	500 × 500	20	Water and farmland	Relatively uniform
(*b*)	500 × 500	20	Mountains and cities	Not uniform
(*c*)	500 × 500	20	Water	Uniform
(*d*)	500 × 500	20	Cities	Not uniform

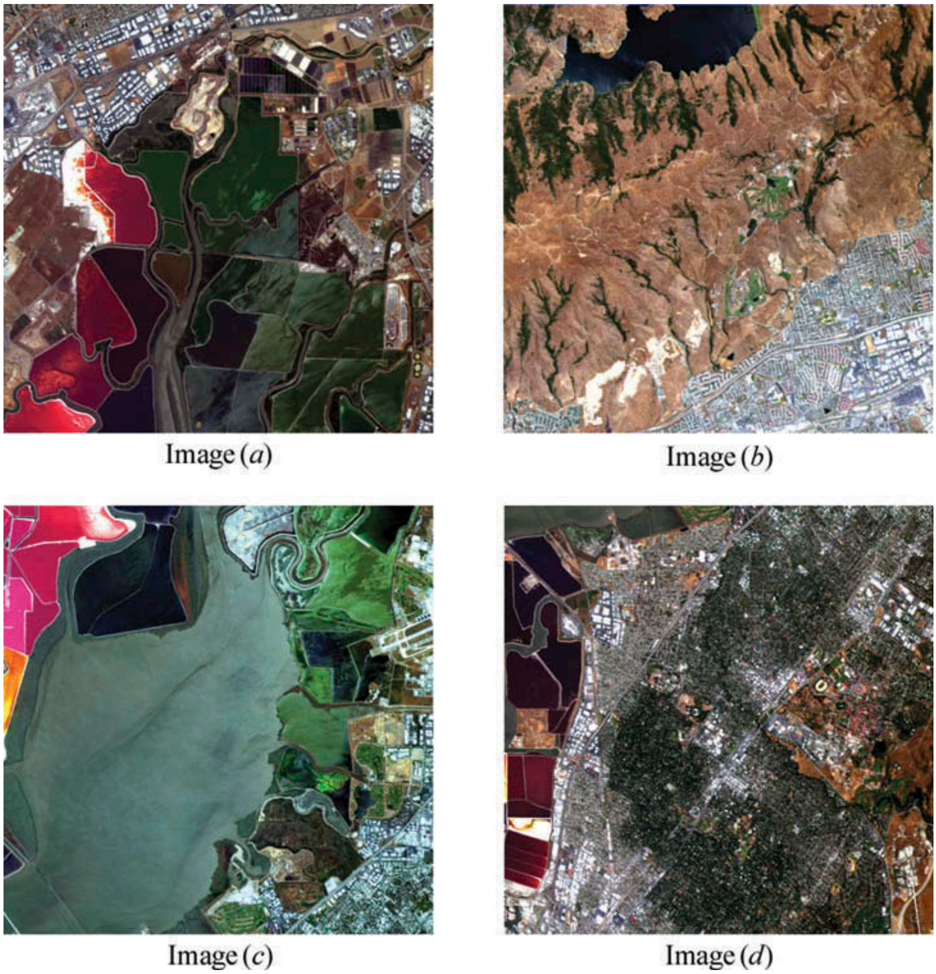

Figure 2. AVIRIS images used in this study. These images are obtained on 20 June 1997. True colour composite of Bands 8, 18 and 30.

4. Results and analysis

According to the reviews and assessments by Gao et al. (2013), Chen and Xue (2000) and Roger and Arnold (1996), the SSDC method is more reliable than other methods for noise estimation in hyperspectral images. In this study, we use AVIRIS images as experimental data. The noise estimation results of SSDC could be used as references for other methods. To verify the improving effect of HRDRS, LMLSD and EELSD are also employed to estimate the noise level of images.

In SSDC, the recommended size of the blocks is 16 × 16 pixels (Roger and Arnold 1996), while in LMLSD and EELSD, a block size of 4 × 4 pixels is used (Gao 1993; Gao, Zhang, Zhang, et al. 2007). The HRDRS method is improved from LMLSD and EELSD, thus a block size of 4 × 4 pixels is implemented in this experiment.

The AVIRIS images described earlier are utilized to test the accuracy of HRDRS and its applicability to different land cover types. Also, because the four images were obtained during the same flight, we can also assess the stability of the method in noise estimation.

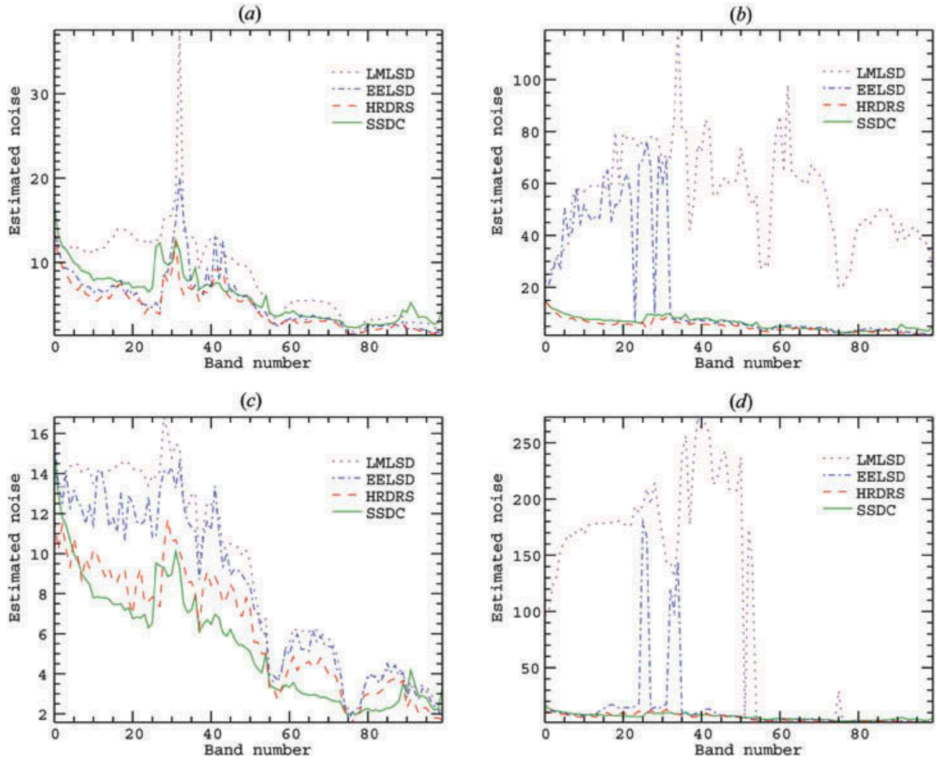

Figure 3. Estimates of the noise for AVIRIS images using LMLSD, EELSD, SSDC and HRDRS, where (*a*), (*b*), (*c*) and (*d*) correspond to the images (*a*), (*b*), (*c*) and (*d*) as shown in Figure 2.

4.1. The accuracy and applicability of HRDRS method

The noise estimation results of four AVIRIS images using the LMLSD, EELSD, SSDC and HRDRS methods are shown in Figure 3.

In all images, the evaluated results of LMLSD have different degrees of deviations compared with the results of SSDC. The deviations are relatively small in images (*a*) and (*c*), which are relatively homogeneous images. However, in images (*b*) and (*d*), which are covered by complex land types, the deviations are extremely large, and the maximum relative deviations are up to 10 and 20 times greater, respectively.

The performance of EELSD is better than LMLSD on the whole, especially in complex images like images (*b*) and (*d*), but it still causes noise overestimation. There are still large deviations between the results of EELSD and those of SSDC for band 1 to band 32 in image (*b*), band 25 to band 26 and band 32 to band 34 in image (*d*).

Unlike LMLSD or EELSD, HRDRS does not produce large deviations in the amount of noise. Even for being applied to complex images like images (*b*) and (*d*), its noise estimation results are still close to the ones of SSDC method.

To quantitatively assess the performance of these methods, taking the results of SSDC as the real noise value, the mean of absolute error (MAE) and standard deviation of absolute error (SDAE) of the noise estimation results using LMLSD, EELSD and HRDRS are calculated.

As shown in Table 2, the MAE and SDAE of the results of HRDRS are less than those of LMLSD and EELSD in almost all the images, which demonstrates that HRDRS is more accurate and stable than LMLSD and EELSD in noise estimation. Moreover, for

Table 2. Accuracy assessments of noise estimation results using LMLSD, EELSD and HRDRS.

Method	(*a*)		(*b*)		(*c*)		(*d*)	
	MAE	SDAE	MAE	SDAE	MAE	SDAE	MAE	SDAE
LMLSD	2.76	3.06	49.95	18.26	3.50	2.34	95.55	93.63
EELSD	1.39	1.63	13.28	21.04	2.69	1.75	8.73	29.42
HRDRS	1.48	1.30	1.24	0.91	1.19	0.72	1.51	1.04

images with different land cover types, the noise estimation results of HRDRS always have low MAE and SDAE value (no more than 1.6), which illustrates that the HRDRS method have a good applicability to images with different land cover types.

According to the preceding analysis, LMLSD and EELSD are prone to be affected by the land cover types in images. They are only suitable for the images mainly composed of homogeneous regions like water and farmland. When they are used for the image containing lots of inhomogeneous land types such as city or mountain, these methods will cause overestimation of image noise. The HRDRS method can overcome this weakness and perform well not only in homogeneous images but also in heterogeneous images. It has a great improvement in the accuracy of noise estimation and is applicable to remote sensing images with different land cover types.

4.2. The stability of HRDRS method

Since the four test images were acquired in the same flight, the image quality and noise level of the four images should be close. That means the noise estimation curves of the four images should be similar in change trend and close in quantity.

The noise estimation results of the four images using HRDRS are shown in Figure 4. Although there are differences between the noise-estimation curves of the four images, the

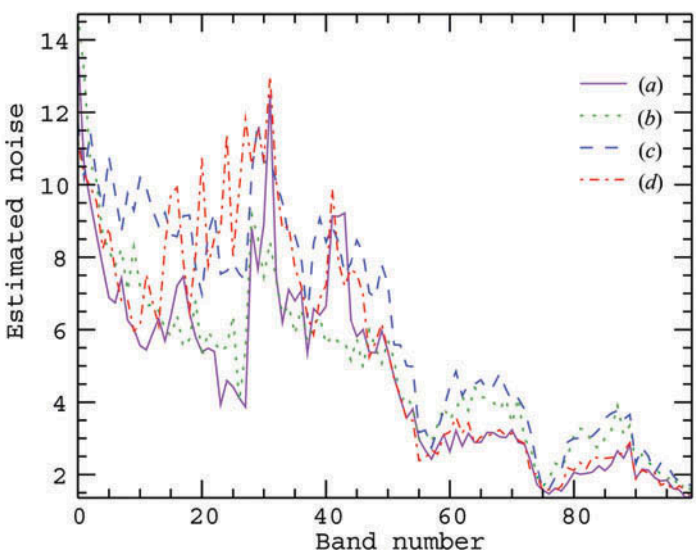

Figure 4. Comparison of the noise evaluated results of images (*a*), (*b*), (*c*) and (*d*) using HRDRS.

change trends of the curves are similar. The noise estimation results in images (*a*) and (*b*) are highly correlated, with the exception of several bands, such as band 30 to band 32 and band 40 to band 45. The differences between the other two curves are mainly concentrated in the first 30 bands; from band 30 onwards, the noise distribution curves are highly comparable.

5. Conclusions

In the article, we analysed the advantages and the disadvantages of the existing noise-estimation methods and proposed a new method for noise estimation of remote sensing images. This method used the theory of LMLSD as a reference and was improved in three aspects: homogeneous regions extracting, residual deviations calculation and optimal noise-estimation interval selection.

Experimental results obtained from four AVIRIS images demonstrated that this new method significantly improved the accuracy of noise estimation and the applicability to complex land cover types. The stability of the algorithm has also been improved. Besides the images mentioned in this article, supplementary images were used to test HRDRS, and the results showed that it performed well in different kinds of remote sensing images, such as single-band and multispectral images. Thus, this new method has a broader applicability than other methods mentioned in this article and can be used for quality evaluation of remote sensing images.

Acknowledgment

The authors would like to thank Dr Muhammad Hasan Ali Baig and Dr Dong Di for the help in English writing. The authors would like to thank Jet Propulsion Laboratory for providing the AVIRIS images.

Funding

This study was supported by the National Natural Science Foundation of China [Project Nos. 61301235 and 41201350].

References

Al-amri, S. S., N. V. Kalyankar, and S. D. Khamitkar. 2010. "A Comparative Study of Removal Noise from Remote Sensing Image." *International Journal of Computer Science Issues (IJCSI)* 7 (1): 32–36.

Canny, J. 1986. "A Computational Approach to Edge Detection." *IEEE Transactions on Pattern Analysis and Machine Intelligence* PAMI-8: 679–698. doi:10.1109/TPAMI.1986.4767851.

Chen, Q. L., and Y. Q. Xue. 2000. "Estimation of Signal-Noise-Ratio from Data Acquired with OMIS (In Chinese)." *Journal of Remote Sensing* 4 (4): 284–288.

Chen, Y. H., Y. Q. Ji, J. K. Zhou, X. H. Chen, and W. M. Shen. 2012. "Computation of Signal-To-Noise Ratio of Airborne Hyperspectral Imaging Spectrometer." In *International Conference on Systems and Informatics (ICSAI)*, Tantai, May 19–20, 1046–1049. IEEE. doi:10.1109/ICSAI.2012.6223191.

Corner, B. R., R. M. Narayanan, and S. E. Reichenbach. 2003. "Noise Estimation in Remote Sensing Imagery Using Data Masking." *International Journal of Remote Sensing* 24 (4): 689–702. doi:10.1080/01431160210164271.

Curran, P. J., and J. L. Dungan. 1989. "Estimation of Signal-To-Noise: A New Procedure Applied to AVIRIS Data." *IEEE Transactions on Geoscience and Remote Sensing* 27 (5): 620–628. doi:10.1109/TGRS.1989.35945.

Gao, B. C. 1993. “An Operational Method for Estimating Signal to Noise Ratios from Data Acquired with Imaging Spectrometers.” *Remote Sensing of Environment* 43 (1): 23–33. doi:10.1016/0034-4257(93)90061-2.

Gao, L. R., Q. Du, B. Zhang, W. Yang, and Y. F. Wu. 2013. “A Comparative Study on Linear Regression-Based Noise Estimation for Hyperspectral Imagery.” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 6 (2): 488–498. doi:10.1109/JSTARS.2012.2227245.

Gao, L. R., B. Zhang, J. T. Wen, and Q. Ran. 2007. “Residual-Scaled Local Standard Deviations Method for Estimating Noise in Hyperspectral Images.” In *International Symposium on Multispectral Image Processing and Pattern Recognition*, Proceedings of SPIE, Vol. 6787, edited by H. Maître, H. Sun, J. G. Liu, and E. Song, Wuhan, October 26–27, 678713. doi:10.1117/12.749122.

Gao, L. R., B. Zhang, X. Zhang, and Q. Shen. 2007. “Study on the Method for Estimating the Noise in Remote Sensing Images Based on Local Standard Deviations (In Chinese).” *Journal of Remote Sensing* 11 (2): 201–208.

Gao, L. R., B. Zhang, X. Zhang, W. J. Zhang, and Q. X. Tong. 2008. “A New Operational Method for Estimating Noise in Hyperspectral Images.” *IEEE Geoscience and Remote Sensing Letters* 5 (1): 83–87. doi:10.1109/LGRS.2007.909927.

Garzelli, A., and F. Nencini. 2009. “Hypercomplex Quality Assessment of Multi/Hyperspectral Images.” *IEEE Geoscience and Remote Sensing Letters* 6 (4): 662–665. doi:10.1109/LGRS.2009.2022650.

Green, R. O., M. L. Eastwood, C. M. Sarture, T. G. Chrien, M. Aronsson, B. J. Chippendale, J. A. Faust, B. E. Pavri, C. J. Chovit, M. Solis, M. R. Olah, and O. Williams. 1998. “Imaging Spectroscopy and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS).” *Remote Sensing of Environment* 65 (3): 227–248. doi:10.1016/S0034-4257(98)00064-9.

Lang, X. P., F. Zhu, Y. M. Hao, and J. J. Ou. 2008. “Integral Image Based Fast Algorithm for Two-Dimensional Otsu Thresholding.” In *2008 Congress on Image and Signal Processing*, Sanya, May 27–30, 677–681. IEEE. doi:10.1109/CISP.2008.179.

Otsu, N. 1979. “A Threshold Selection Method from Gray-Level Histograms.” *IEEE Transactions on Systems, Man and Cybernetics* 9 (1): 62–66. doi:10.1109/TSMC.1979.4310076.

Roger, R. E., and J. F. Arnold. 1996. “Reliably Estimating the Noise in AVIRIS Hyperspectral Images.” *International Journal of Remote Sensing* 17 (10): 1951–1962. doi:10.1080/01431169608948750.

Sezgin, M., and B. Sankur. 2004. “Survey over Image Thresholding Techniques and Quantitative Performance Evaluation.” *Journal of Electronic Imaging* 13 (1): 146–168. doi:10.1117/1.1631315.

Van der Meer, F. D., and S. M. de Jong. 2001. *Imaging Spectrometry: Basic Principles and Prospective Applications*, 35–38. Dordrecht: Springer.

Wang, Z., and A. C. Bovik. 2002. “A Universal Image Quality Index.” *IEEE Signal Processing Letters* 9 (3): 81–84. doi:10.1109/97.995823.

Wang, Z., A. C. Bovik, and L. G. Lu. 2002. “Why Is Image Quality Assessment so Difficult?” In *2002 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Orlando, FL, May 13–17, 3313–3316. doi:10.1109/ICASSP.2002.5745362.

Zhu, X. W., X. H. Li, Z. Y. Li, and B. Zhu. 2012. “Study on Signal-To-Noise Ratio Algorithms Based on No-Reference Image Quality Assessment.” In *2012 International Conference on Systems and Informatics (ICSAI)*, Yantai, May 19–20, 1755–1759. IEEE. doi:10.1109/ICSAI.2012.6223383.