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Estimation of Signal to Noise Ratio for Unsupervised Hyperspectral Images

Stima del rapporto segnale rumore per immagini iperspettrali

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In copertina Immagine composta in True Colour per il VNIR (particolare)

Estimation of Signal to Noise Ratio for Unsupervised Hyperspectral Images

Hyperspectral sensors have become a standard technology used in the techniques of observation by satellite and aerial platform for observing the terrestrial ecosystem with particular interest in the detection and identification of minerals, vegetation, materials and artificial environments. The detection of real materials depends on the coverage spectral resolution and signal to noise ratio of the spectrometer itself, as well as the density of the material and the absorption characteristics for the material in the region of wavelength measured. The signal to noise ratio in particular is one of the parameters that need to be estimated to establish the quality of images acquired by these systems.

In this contribution a method to estimate the Signal to Noise Ratio (SNR) for unsupervised hyperspectral images has been investigated.

The method uses the computation of local means and local standard deviations of small homogeneous blocks in order to define respectively the average signal and the mean noise of the images. If the noise may be considered mainly addictive the local standard deviation may be considered as the mean noise of image. This method uses all the spatial information contained in the image scene giving a representative SNR of entire image.

The technique has been engineered in IDL environment and applied to hyperspectral data of HYPER-SIMGA sensor, developed in the frame of AIRFIRE Project for wildfire detection by airborne remote sensing data.

The SNR results point out that HYPER-SIMGA SWIR images are quite noisy and the spectral range that has to be taken into account for data analysis is from 1000 to 1700 nm.

L'uso di sensori iperspettrali è ormai uno standard tecnologico impiegato nelle tecniche di osservazione da satellite e da piattaforma aerea per l'osservazione dell'ecosistema terrestre con particolare interesse all'individuazione e identificazione di minerali, vegetazione, materiali e ambienti di origine artificiale. La rilevazione reale dei materiali dipende dalla copertura spettrale, dalla risoluzione e dal rapporto segnale-rumore dello spettrometro stesso, oltre che della densità del materiale e dalle caratteristiche di assorbimento per quel materiale nella regione di lunghezza d'onda misurata. Il rapporto segnale-rumore, in particolare, è uno dei parametri che devono essere stimati per stabilire la qualità delle immagini acquisite da questi sistemi.

Nel presente lavoro è stata investigata una tecnica per la stima del Rapporto Segnale Rumore (SNR) per immagini iperspettrali delle quali non si ha informazioni sul rumore. Il metodo utilizza il calcolo delle medie e delle deviazioni standard locali di piccoli blocchi omogenei in cui è suddivisa l'immagine in modo di definire, rispettivamente, il segnale medio e il rumore medio. Nel caso in cui il rumore è principalmente di natura additiva la deviazione standard locale descrive con buona approssimazione il rumore medio dell'immagine. La tecnica utilizza tutte le informazioni spaziali di una scena fornendo una stima rappresentativa dell'SNR per tutta l'immagine.

La tecnica è stata automatizzata in ambiente IDL e applicata a dati iperspettrali del sensore HYPER-SIMGA, sviluppato nell'ambito del progetto AIRFIRE per la localizzazione di incendi tramite l'analisi di dati iperspettrali acquisiti da aereo.

I risultati evidenziano che il segnale HYPER-SIMGA nello SWIR è piuttosto rumoroso e l'intervallo spettrale che deve essere preso in considerazione per l'analisi dei dati è da 1000 fino a 1700 nm.

Introduction

In the frame of AIRFIRE project (ESA contract CN/20090) an imaging spectrometer [Fiorani et al. 2007] HYPER-SIMGA, realized by Selex SAS Galileo was mounted on an ultra light plane and tested on small scale wild fire [Amici, 2009]. The main objective of the project was to test the system and to validate and to assess the results obtainable through the most relevant satellite observation techniques, against the high resolution fire mapping information derived from a dedicated SIM-GA spectral airborne campaign.
The HYPER-SIMGA is a prototype and when it was used for the AIRFIRE campaign its laboratory characterization was not yet completed. Tests about spectral and spatial calibration were completed, radiometric calibration was in progress (completed by the authors for the visible channel) and much information about sensors performances were not yet officially delivered by the producer. The sensor was further mounted on an ultra light aircraft showing some problems of stability. For these reasons, since we don't have any information about the characteristics of signal and in order to evaluate the quality of imaging data and to analyze the data quantitatively, the Signal to Noise Ratio (SNR) needs to be estimated.
In this work the signal is considered to be a quantity measured by an imaging spectrometer. The noise is a quantity describing the random variability of the signal.
Based on the observations that many high spatial resolution images contain a large number of homogeneous areas, Lee and Hoppel [1989] have developed a method for estimation of SNRs of imaging data. The method consists in dividing the entire image in small blocks; the mean and variance for each block is computed. A scatter plot of the variances versus the squares of means of all blocks is obtained. The straight line that interpolates the maximum number of points in the scatter plot describes the noise characteristics of the image. The method permits to characterize both the additive noise (line offset), which is independent by the signal, and the multiplicative noise (line slope), which is proportional to signal.
Starting from the hypothesis of additive noise, Gao B.C. [1993] implemented a method for the estimation of the SNR of unsupervised hyperspectral remote sensed data containing a large number of small homogeneous blocks by using local means and local standard deviations computation. The method has been applied and verified on AVIRIS images.
Since no information about noise of HYPER-SIMGA images were available the method may be suitable for the SNR evaluation. We have automated the technique by developing an IDL processor and we utilized ENVI software for image pre-processing and visualizing.
By using the tool we have verified the applicability of method and an estimation of SNR for HYPER-SIMGA has been evaluated.

1. Method description

The image is divided in small homogeneous blocks having N=M*M pixels [Coakley and Bretherton, 1982]. For each block the Local Mean (LM) is computed:

$$LM(\lambda) = \frac{1}{N}\sum_{i=1}^{i=N} S_i(\lambda) \qquad (1)$$

where S_i is the signal corresponding to the ith pixel for each band.
The Local Standard Deviation (LSD) for each block is computed by

$$LSD(\lambda) = \left[\frac{1}{(N-1)}\sum_{i=1}^{i=N}\left(S_i(\lambda) - LM\right)^2\right]^{1/2} \qquad (2)$$

The computed LSDs provide information about the level of noise in the image. The following step consists in calculate the LMs and LSDs of signal for each band on all blocks image.
Then the LSDs of all blocks are grouped in bins, the number of ranges in which fall LSD values, and the bin with the largest number of blocks corresponds to the mean noise signal of the image.
Taking into account the additively assumption, the spectral SNR estimation can be expressed by the following equation:

$$SNR(\lambda) = \frac{meansignal(\lambda)}{meannoise(\lambda)} \qquad (3)$$

where *meansignal*(λ) is the mean calculated over the image for each wavelength, *meannoise*(λ) is the quantity described previously.
In the following section will be described the method applied to HYPER-SIMGA hyperspectral images.

2. Data analysis

Data analyzed were acquired from SIMGA sensor (a modern-generation push-broom image spectrometer) manufactured by Selex Galileo, in Italy, that covers a spectral range from Visible Near Infrared (VNIR) to Short Wave Infrared (SWIR).
The VNIR instrument features 512 bands in the interval 400-1000 nm, with spectral resolution 1.2 nm, and is equipped with a 1024x512 CCD array spanning the across track and spectral direction, respectively. Raw data are acquired with a 12 bit ADC. The ground pixel size is in the order of 5 m. The SWIR instrument features 256 bands in the inter-

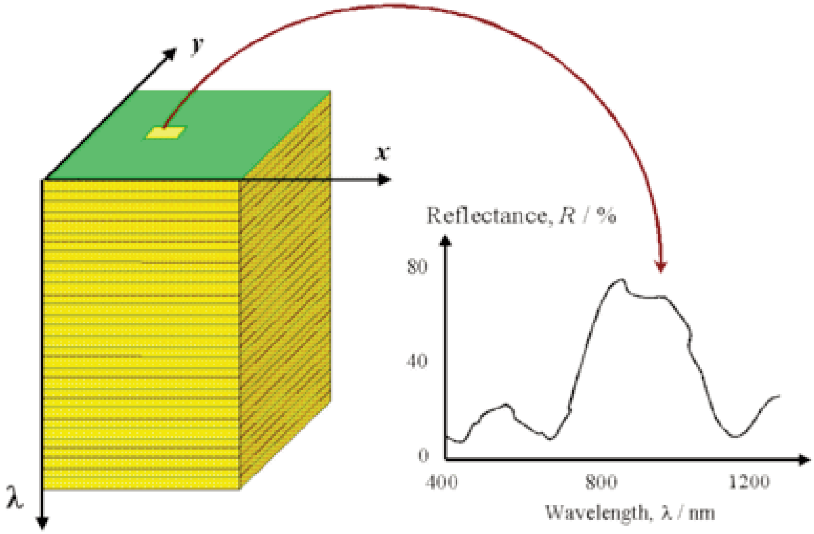

Figure 1 An illustration of a hyperspectral image cube. The hyperspectral image data usually consists of over a hundred contiguous spectral bands, forming a three-dimensional (two spatial dimensions and one spectral dimension) image cube. Each pixel is associated with a complete spectrum of the selected area.
Figura 1 Descrizione di una immagine iperspettrale (cubo). Essa consiste di centinaia di bande spettrali contigue che formano una immagine tridimensionale (due dimensioni spaziali ed una spettrale). Ogni pixel è associato ad uno spettro completo della scena.

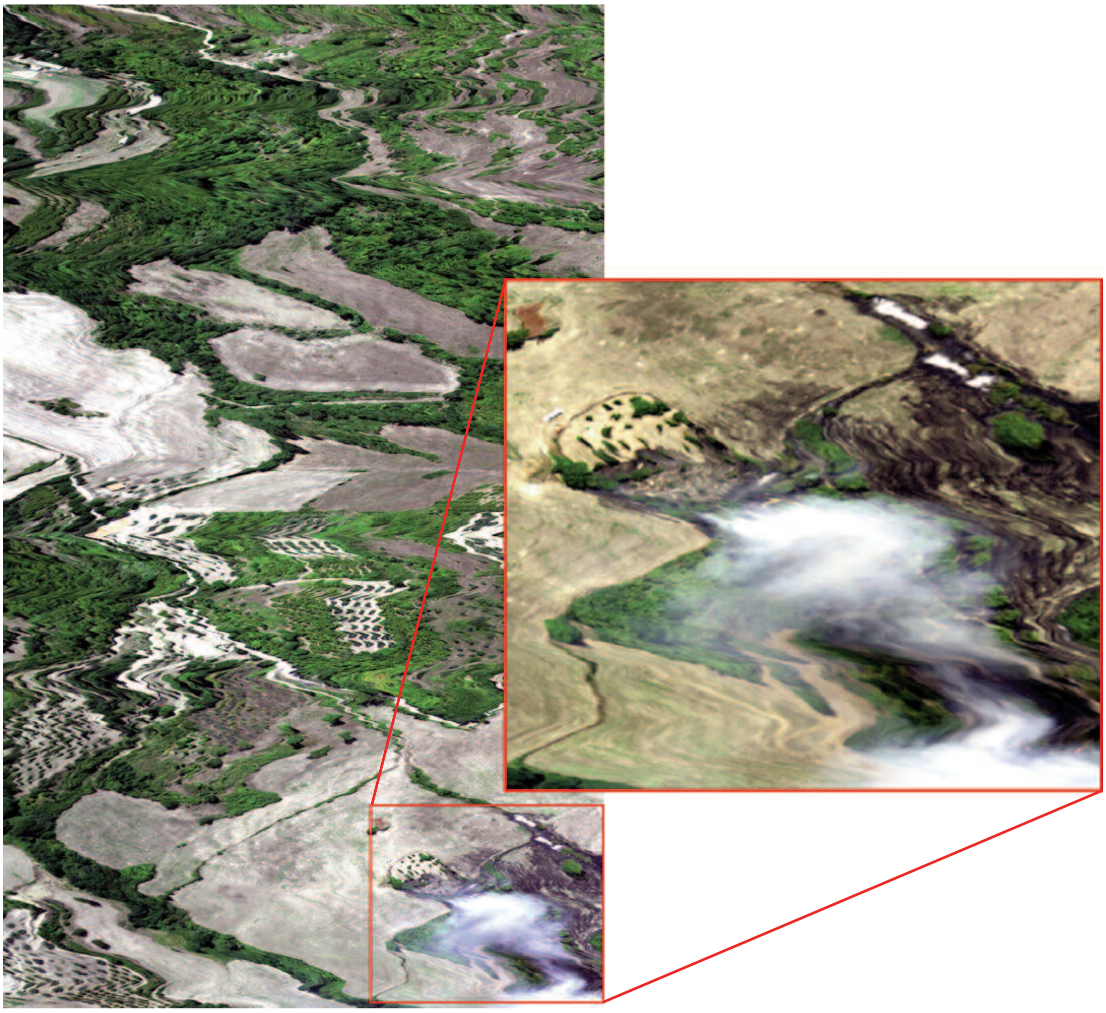

Figure 2 TVNIR True Colour composition. R=ch.198, 621.15 nm; G=ch.153,569.09 nm; B=ch.92, 499.81 nm plus sub area selected.
Figura 2 Immagine composta in True Colour per il VNIR. R=ch.198, 621.15 nm; G=ch.153,569.09 nm; B=ch.92, 499.81 nm e sotto area selezionata.

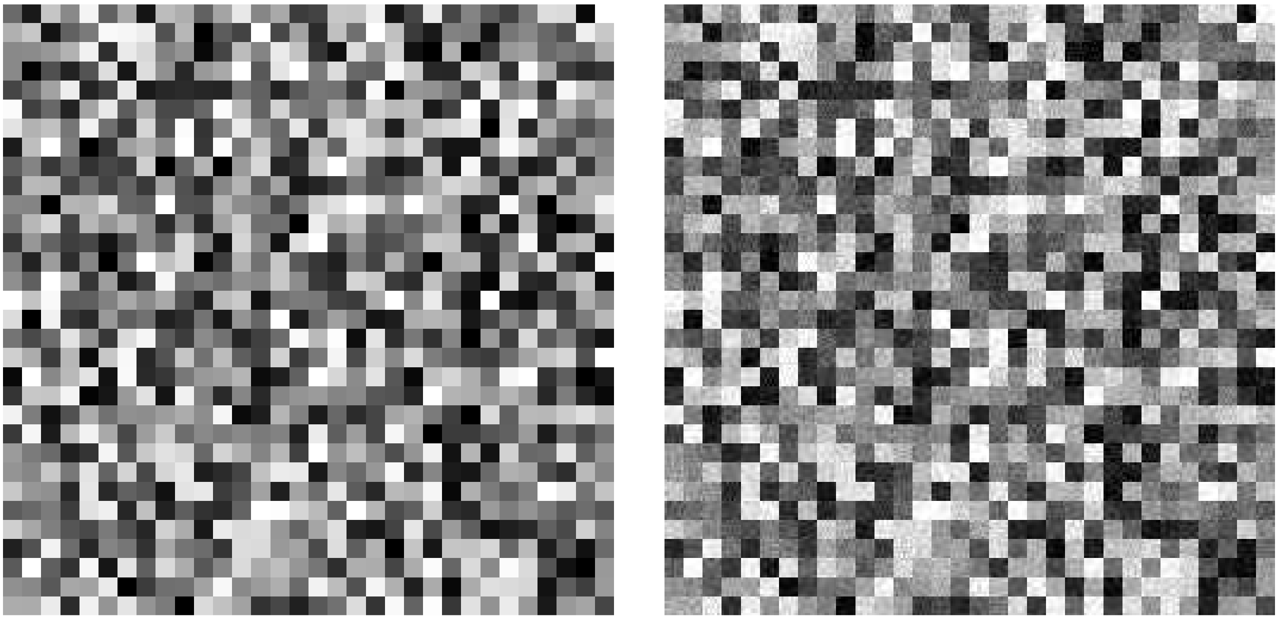

Figure 3a and 3b 256x256 simulated checkerboard pattern image (a) and the same image plus gaussian noise image (b) having 0 mean and standard deviation of 5.0.
Figura 3a e 3b Immagine 256x256 pixel con pattern a scacchiera (a) e stessa immagine sommata ad una immagine con distribuzione gaussiana a media 0 e deviazione standard 5.0.

val 1000- 2500 nm, with spectral resolution 5.4 nm, and is equipped with a 320x256 array of detectors in InGaAs technology. Raw data are acquired with a 14 bit ADC. The ground pixel size is in the order of 10 m.
The final result is a three-dimensional data set (named Data Cube) that correlates each ground pixel with its corresponding electromagnetic spectrum (fig. 1).
Figure 2 shows a VNIR true colour image acquired with HYPER-SIMGA spectrometer. It relates to a wildfire occurred on August 4th 2006, close Magliano-Campagnano

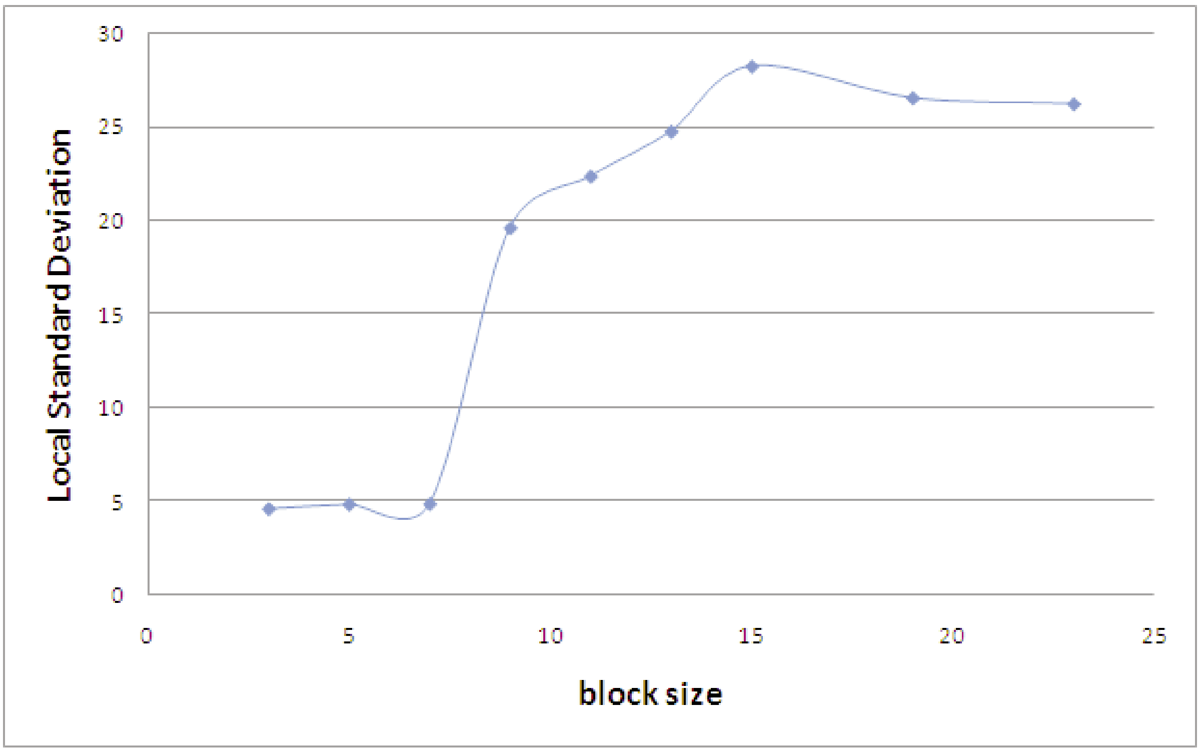

Figure 3c LSD estimation varying block dimension.
Figura 3c Stima delle Deviazioni Standard Locali al variare delle dimensioni del blocco.

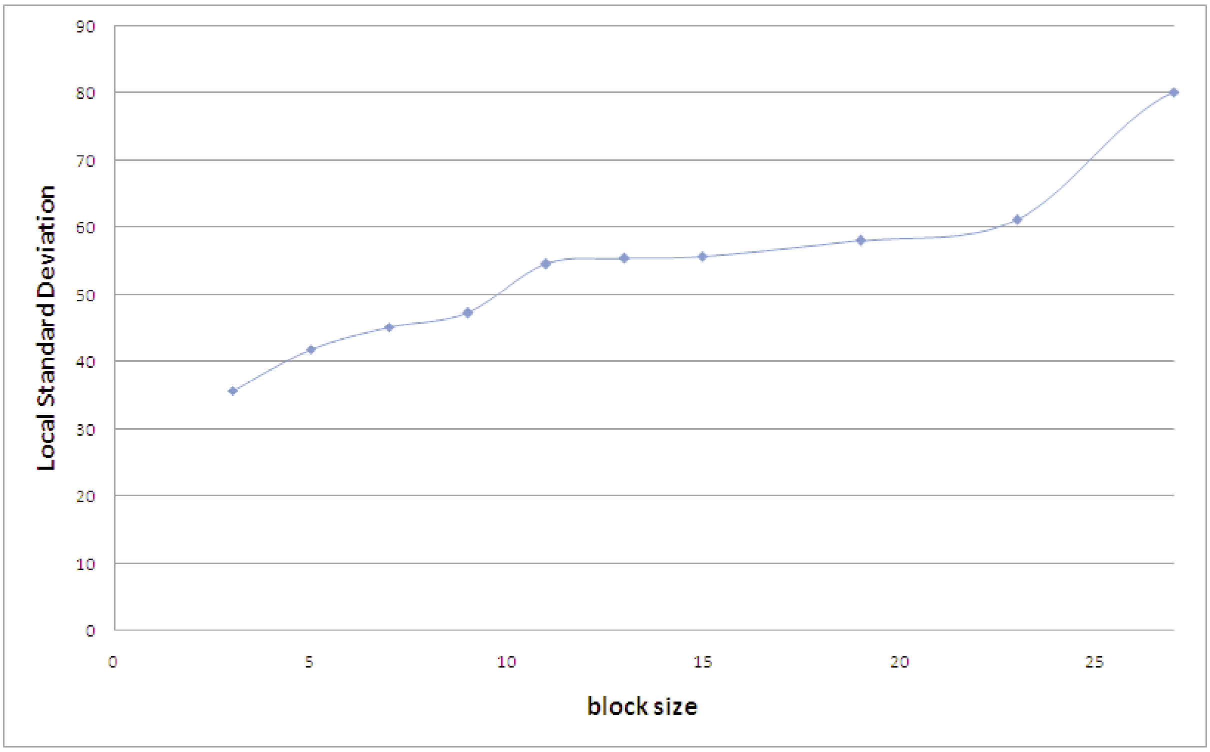

Figure 4 LSD estimation varying block dimension for test image plus Gaussian noise, band at 569 nm.
Figura 4 Deviazione Standard Locale per differenti dimensioni della finestra per l'immagine di test più il rumore gaussiano nella banda a 569 nm.

villages, in north of Rome (N 42° 08' 41.641" E 12° 25' 50.237"). The image is an array of 1024 x 1708 pixels each one with 512 spectral values.
Due to limit of IDL in allocation of memory we resized the image focusing on a smaller area around the area of interest (wildfires). The resized image is a 400x400 pixel image has been (figure 2) obtained applying an ENVI-Resize routine, using nearest neighbour interpolation method, in order to preserve image spectral information.
The IDL processor computes the mean and LSD data cube by using equations (1) and (2) applying the respectively texture filters [Anys, H. et al, 1994] and the SNR applying equation (3). Input parameters are the dimension of blocks in pixel units and the number of bins to group LSD values.
We tested the performance of the method applying it on a simulated image having a checkerboard pattern plus gaussian noise. We generated an image having 32x32 pixels with value uniformly distributed between 100 and 200 and zoomed it up a 8 by 8 pixel basis creating a 256x256 pixels image having a checkerboard pattern containing a homogenous area of 8 by 8 pixels (Fig. 3a). Finally we added to it a gaussian noise image with mean=0 and standard deviation= 5.0 (Fig 3b).
We applied the processor for noise estimation described below starting from 3x3 to 31x31 odd block dimension.
As shown in fig. 3c the noise assessment is reasonable until homogeneity condition is respected.
The simulation shows the usefulness of the method and points out that a block size that not assure homogeneity may lead to an over estimation of image noise.
In order to avoid texture features in image to affect homogeneity of imaging blocks and subsequently SNR assessment, it is important to choose the right block dimension. We extracted the band at 569 nm from image, add to it a Gaussian noise (characterized by mean=0 and standard deviation=35) and applied the method for different block sizes. Figure 4 depicts LSD computed for different block dimensions and as we can see larger block sizes imply less homogeneous areas and noise overestimation therefore size of 3x3 gives the value that assures the homogeneity condition and reasonable SNR assessment.
Within the minimum and the maximum of the LSDs, a number bins with equal width is set up, 150 bins for a 400x400 px image, [Gao, B. C., 1993].
A scatter plot of the LSDs versus LMs is calculated to estimate the noise characteristics of the signal.
As example we report the scatter plot for a single band of the VNIR image (figure 5a) and scatter plot for a single band of the SWIR image (figure 6a).
We can note (figure 5a) that the points with LSDs greater than a certain value are considered to correspond to inhomogeneous blocks (green cluster). Many points are clustered around a horizontal line. They correspond to homogene-

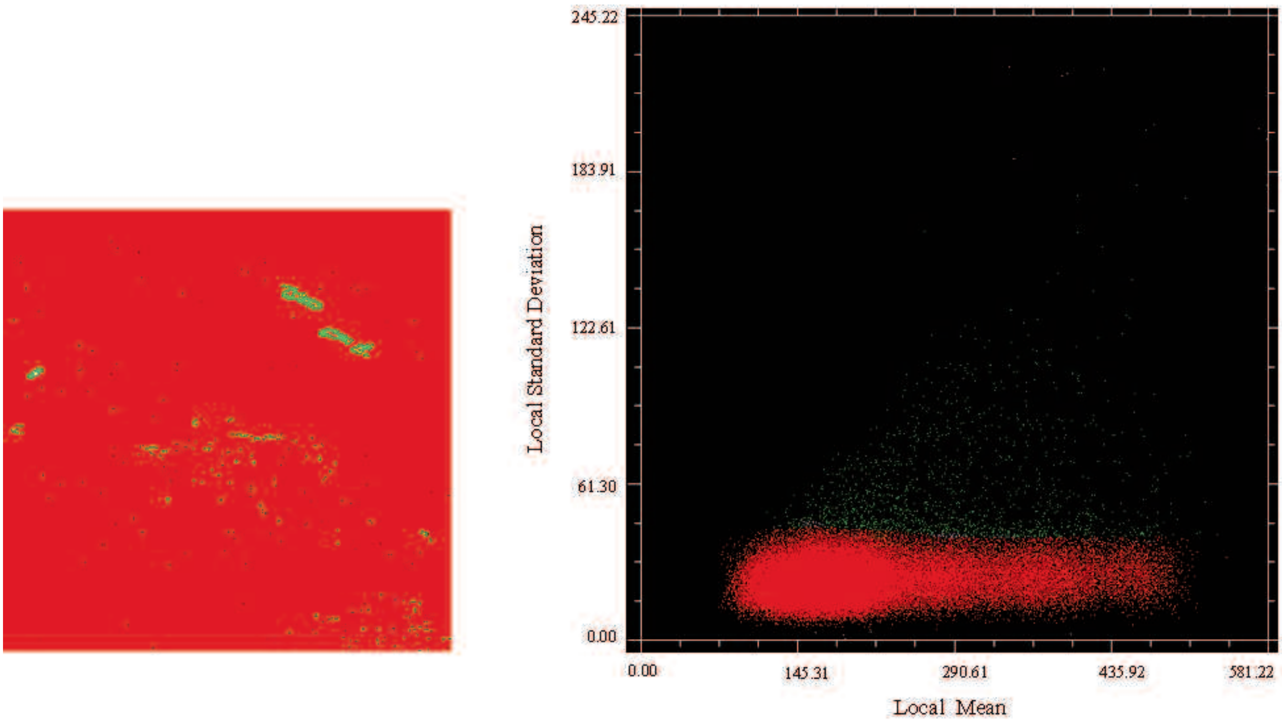

Figure 5a The visible image (on the left) shows the two clusters: the red area corresponds to homogeneous blocks, the green area corresponds to inhomogeneous blocks. The scatter plot (on the right) shows the local standard deviations versus local means for a 3x3 pixels block size into the selected image.
Figura 5a L'immagine nel Visibile mostra due *cluster*: l'area in rosso corrisponde ai blocchi omogenei, quella verde ai blocchi disomegenei. Uno *scatter plot* (destra) mostra le deviazioni standard locali in funzione delle medie locali per blocchi di dimensione 3x3 pixel per l'immagine selezionata.

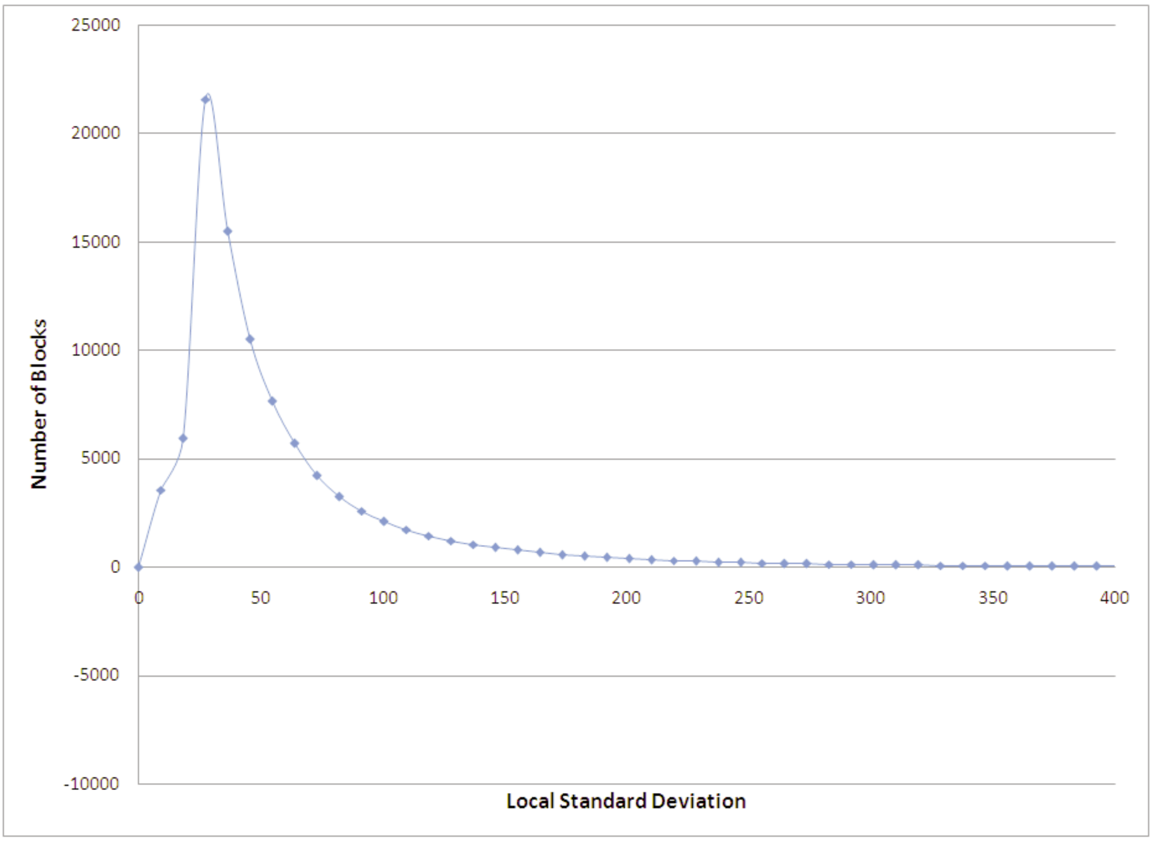

Figure 5b Number of blocks on layers of local standard deviations.
Figura 5b Numero di blocchi in funzione della deviazione standard locale.

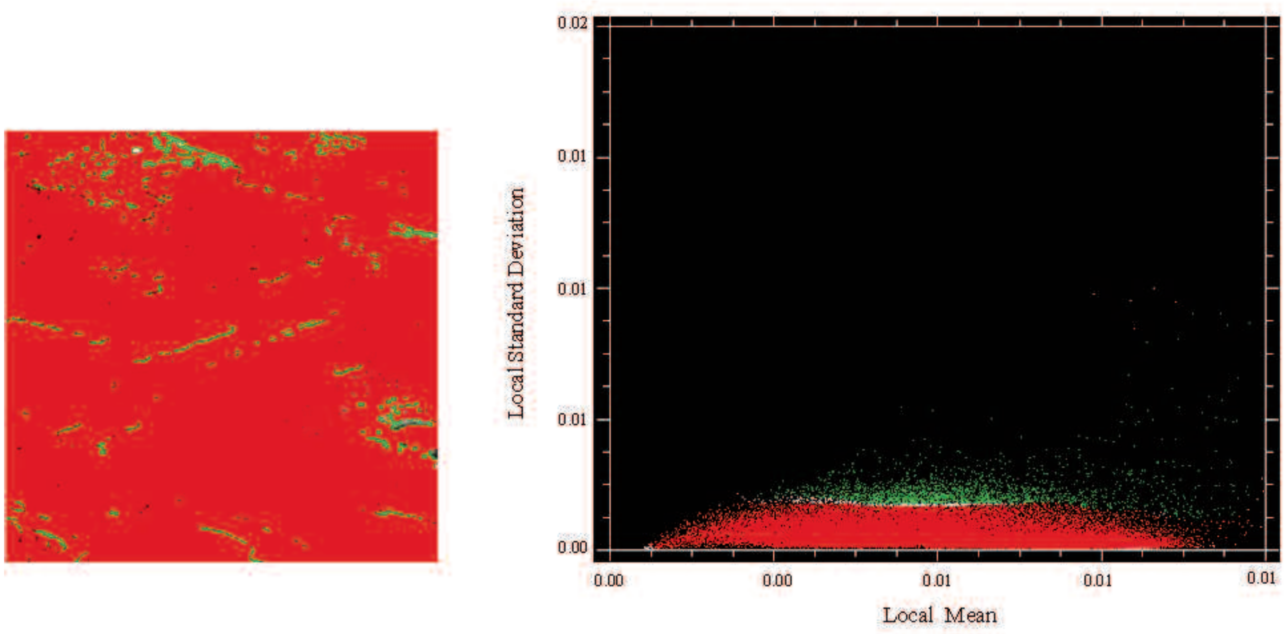

Figure 6a SWIR image on left side shows the two clusters: red area corresponds to homogeneous blocks. A scatter plot (on right) of local standard deviations versus local means for a block size 3x3 pixels for the image.
Figura 6a L'immagine nello SWIR a sinistra mostra due *cluster*: l'area rossa corrisponde ai blocchi omogenei. A destra è illustrato lo *scatter plot* delle deviazioni standard locali rispetto alle medie locali con dimensione del blocco dell'immagine di 3x3 pixels.

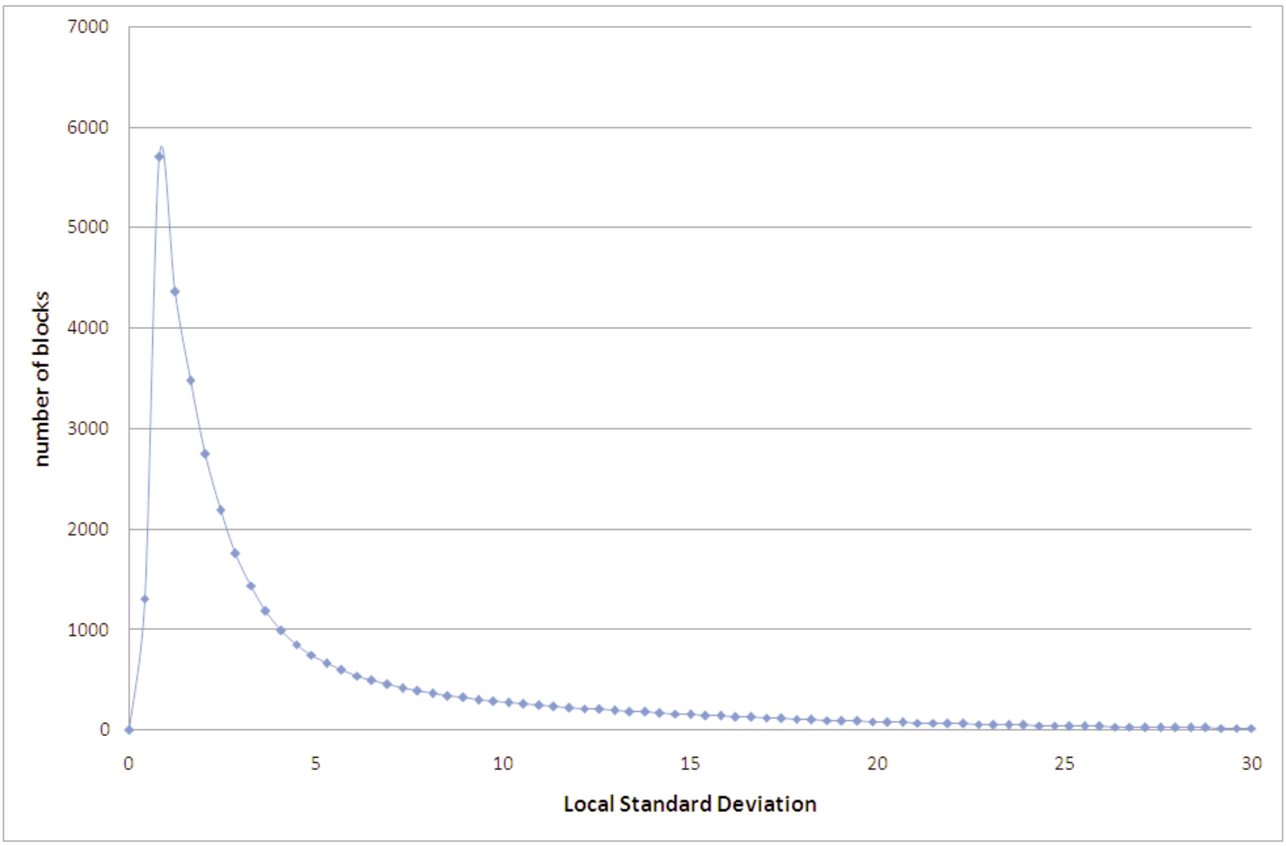

Figure 6b Number of blocks on layers of local standard deviations.
Figura 6b Numero di blocchi rispetto alla deviazione standard locale.

ous blocks containing information on the noise in the image (red cluster). Scatterplot also indicates that noise is approximately independent from signal confirming the noise additively assumption.
The IDL program computes also the histogram of blocks on LSD bins for the entire image that is represented in figure 5b. It describes the distribution of number of blocks averaged all over the bands on LSD bins for the image with a block size of 3x3. The bin with the largest number of blocks has a LSD value of 27.39 and because the noise is mainly additive it can be considered the mean noise of entire image.
As regards SWIR (figure 6a) many points have a LSD value around a horizontal line. They correspond to homogeneous blocks containing information on the noise in the image (red cluster). Points far from this alignment correspond to inhomogeneous blocks (green cluster). The horizontal line distribution indicates also in this case that the noise is approximately independent from signal confirming the noise additively hypothesis.
The histogram on figure 5b, averaged all over the bands, shows a mean noise of 0.8 for SWIR image.

3. Results

The method has been applied both to VNIR and SWIR data cubes. The test case selected was the image registered on 04 Ago 2006 13:42 GMT.
Figure 7 shows the spectrum obtained averaging all the spectra over the scene selected for VNIR (left) and SWIR (right) images. The Oxygen absorption band at 760 nm and water vapour band at 940 nm are clearly visible. The two spikes at

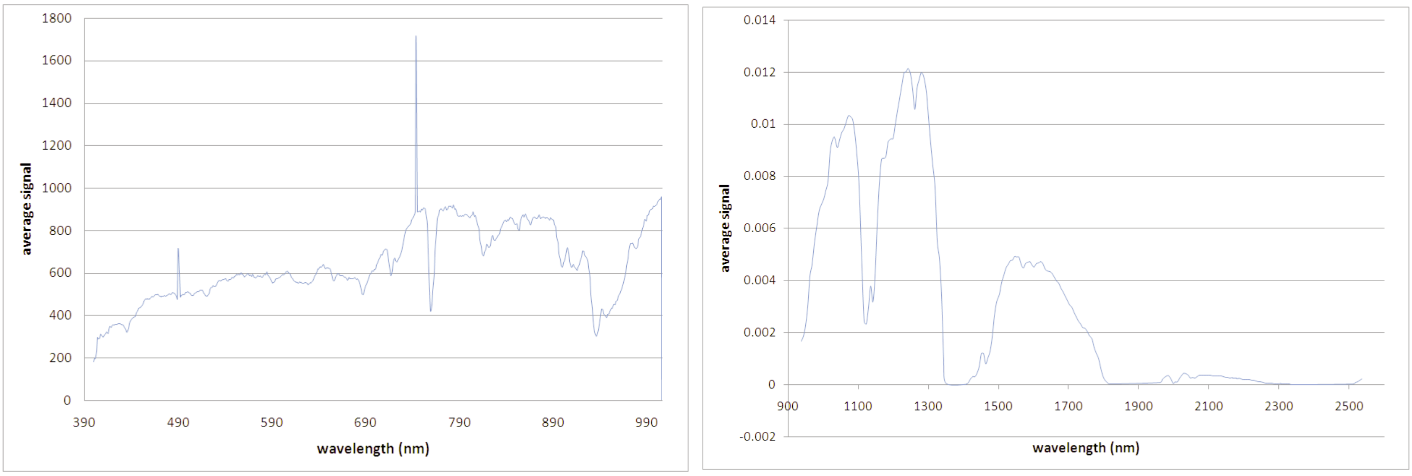

Figure 7 Average spectra for VNIR image (left plot) and average spectra for SWIR image (right plot).
Figura 7 Spettro medio per l'immagine nel VNIR (sinistra) e spettro medio nello SWIR (destra).

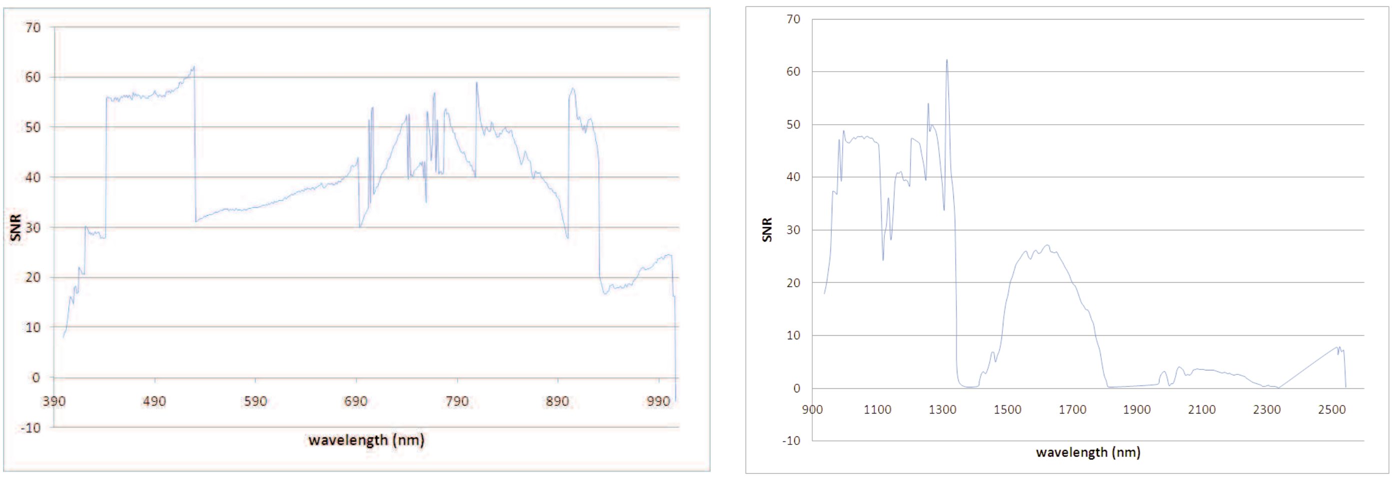

Figure 8 Signal to noise ratios for VNIR (left) and SWIR (right) image.
Figura 8 Rapporto segnale-rumore dell'immagine nel VNIR (sinistra) e nello SWIR (destra).

489 and 743 nm are two CCD bad pixels. The SWIR plot shows the mean signal: 1140, 1380 and 1870 nm correspond to water vapour absorption bands.
The SNR for the both channels is showed in figure 8.
The higher values of SNR (values between 55 and 62) occur in two wavelength intervals: between 440 and 530 nm and about 530 and 900 nm. The other bands exhibit values from 30 to 60. From 900 nm to 940 nm the SNR has mean values of 50. The SNR for the SWIR data are between 40 and 50 from 950-1330 nm. Between 1300-2500 nm the values decrease dramatically from 30 (max value) to 8.
As we can see HYPER-SIMGA SWIR images are quite noisy and spectral range that have to be taken into account for data analysis is from 1000 to 1700nm.

Conclusions

In this work a method to estimate the Signal to Noise Ratio (SNR) for unsupervised hyperspectral images has been investigated.
The method, that uses the computation of local means and local standard deviations of small homogeneous blocks in order to define respectively the average signal and the mean noise of the images, has been engineered. A processor has been developed in ENVI-IDL environment and used to process hyperspectral data from a very high spectral resolution sensor (HYPER-SIMGA).
Thanks to the SNR analysis the low signal at SWIR bands from 1900 to 2500 nm may be justified.
These results encourage the authors to applied and verify the method on different hyperspectral -multispectral sensors and SAR.

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Abbreviations

ADC Analogue Digital Converter

AIRFIRE An airborne campaign for the validation and calibration of fire monitoring system based on satellite data processing

AVIRIS Airborne Visible/Infrared Imaging Spectrometer

CCD Charge-Coupled Device

ESA European Space Agency

ENVI ENvironment for Visualizing Images

HYPER-SIMGA Hyperspectral - Sistema Iperspettrale Multisensoriale Galileo Avionica

IDL Interactive Data Language

InGaAs Indium gallium arsenide

LM Local Mean

LSD Local Standard Deviation

SNR Signal to Noise Ratio

SWIR Short Wave Infrared

VNIR Visible Near Infrared

Indice

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