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IMAGE ENHANCEMENT USING MINIMUM NOISE FRACTION (MNF) IN UM EL-GURUF AREA, NORTH EASTERN DESERT, EGYPT

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تحسين جودة صور الأقمار الاصطناعية باستخدام معامل تصغير التشويش فى منطقة أم الجروف، شمال الصحراء الشرقية، مصر

الخلاصـة: كان الغرض الرئيسى من هذا البحث هو تطبيق أسلوب الحد الأدنى من التشويش على صور الأقمار الاصطناعية لمنطقة جبل أم الجروف فى الصحراء الشرقية شمال مصر من أجل إزالة التشويش، مما يعزز جودة الصورة. ويستخدم أسلوب الحد الأدنى من التشويش لتقليل كمية البيانات شديدة الطيفية من خلال فصل التشويش عن البيانات الأساسية فى الصور. وأسلوب الحد الأدنى يعمل على تحويل البيانات إلى ترتيب جديد تكون مصفوفة التغاير المعبرة عن التشويش هى مصفوفة الوحدة يتبعه تحويل المكون الرئيسى للترتيب الجديد. والصعوبة التى تواجه تطبيق هذه التقنية تكمن فى العثور على مصفوفات التغاير فمصفوفة التغاير للصورة الرمادية يمكن استخلاصها بسهولة مثل مصفوفة عينة التغاير من البيانات ولكن الحصول على مصفوفة التغاير للتشويش أكثر تعقيداً. وأظهرت النتائج أن الصور التى تمت تصفيتها باستخدام أسلوب الحد الأدنى هى المتفوقة فى الحد من المشارب و التشويش.

ABSTRACT: *The main purpose of this study is to apply the minimum noise fraction (MNF) method on the satellite images of Gabal Um El-Guruf area in the north eastern desert of Egypt in order to remove its noise which enhances image quality.*

A minimum noise fraction (MNF) transformation is used to reduce the dimensionality of the hyper-spectral data by segregating the noise in the data. The MNF transform is equivalent to a transformation of the data to a coordinate system in which the noise covariance matrix is the identity matrix followed by a principal component transformation. The difficulty in applying the MNF technique lies in finding these covariance matrices. The grey level covariance matrix can be readily derived as the sample covariance matrix of the data and the noise covariance matrix is more complex to assess. The results show that images filtered using the MNF are superior in reducing stripes and noise.

INTRODUCTION

Hyper-spectral images provide a powerful tool as the wave spectrum is finely discretized using hundreds of channels on a scanner. The large dimensionality of a hyper-spectral dataset often requires a data transformation such as principal components analysis (PCA) or the singular value decomposition (SVD) to reduce the number of variables, or bands, within an image prior to further processing. Furthermore, these images tend to be noisy as a result of the fine discretization and other factors such as the method of acquisition (small aircraft). Green et al. (1988), was the first to propose the maximum noise transform (alternately called the minimum noise transform or simply MNF) to align a dataset in order of decreasing signal-to-noise ratio (SNR) using an eigen-value decomposition similar to PCA. Lee et al (1990), equivalently defined the MNF (or noise adjusted PCA) as two PCA transformations, and used the MNF to reduce the noise level in an image. The MNF can be used to reduce noise and the number of dimensions in an image. MNF was originally developed to de-noise multispectral satellite images and was more recently applied to multivariate time series. A necessary condition for solution to the MNF variational problem may be formulated as a generalized eigenvector problem. This problem is reformulated as a pair of standard eigenvector decompositions via a technique referred to as Noise Adjusted Principal Component Analysis.

One of the most famous methods used to reduce image noise is the principle component analysis (PCA). PCA transform multidimensional image data into a new, uncorrelated co-ordinate system or vector space. It produces a space in which the data have maximum variance along its first axis, the next largest variance along a second mutually orthogonal axis and so on. Sometimes even the lower-order PC's may contain valuable information. The later principal components would be expected, in general, to show little variance. These could be considered therefore to contribute little to separability and could be ignored, thereby reducing the essential dimensionality of the classification space and thus improving classification speed. Stated differently, the purpose of this process is to compress all the information contained in an original n– band data set into fewer than n “new bands” or components. The components are then used in lieu of the original data. These transformations may be applied as a preprocessing procedure prior to automate classification process of the data.

According to Townshend (1984), Principal components do not always produce components of decreasing image quality with increasing component number. While working with spatial data, the maximization of variance across bands is not an optimal approach if the issue is ordering in term of image quality rather than variance. One of the most common measures of image quality is the signal-to-noise ratio, thus instead of choosing new components to maximize variance, as the principal. An increase in signal to noise ratio can be obtained by reducing the noise and retaining the signal components transform does, the MNF transform chooses components to maximize the signal-to-noise ratio. This transformation can be defined in several ways. It can be shown that the same set of eigenvectors is obtained by procedures that maximize the signal-to-noise ratio and the noise fraction. The application of the MNF transformation requires estimates of the signal and noise covariance matrices. MNF number one is the linear combination of the original bands that contains the minimum signal-to-noise ratio. A higher order MNF is the linear combination of the original bands that contains minimum signal-to-noise ratio subject to the constraint that it is orthogonal to the lower order MNF.

The MNF transform is essentially two cascaded Principal Components transformations. The first transformation, based on an estimated noise covariance matrix, de-correlates and rescales the noise in the data. This first step results in transformed data in which the noise has unit variance and no band-to-band correlations. The second step is a standard PCA of the noise-whitened data. For the purposes of further spectral processing, the inherent dimensionality of the data is determined by examination of the final eigen-values and the associated images. The data space can be divided into two parts: one part associated with large eigen-values and coherent eigen-images, and a complementary part with near-unity eigen-values and noise-dominated images. By using only the coherent portions, the noise is separated from the data, thus improving spectral processing results.

The MNF Transform can also be used to remove noise from data by performing a forward transform, determining which bands contain the coherent images (by examining the images and eigen-values), and running an inverse MNF transform using a spectral subset to include only the “good" bands, or smoothing the noisy bands before the inverse.

Thus the main difference between PCA and MNF is that the MNF considers the noise while the PCA considers the data variation. It results in an ordering that reflects the image quality. The MNF transformation can be subdivided in four stages: a) obtaining a noise sample; b) formulation of a noise fraction index; c) implementation of a linear transformation function as PCA; and d) inversion of MNF considering only signs information.

METHODS

The procedure was first introduced by Green et al. (1988) in continuation of the work on minimum/ maximum autocorrelation factors by Switzer and Green (1984). The MNF transformation can be mathematically explained as follows:

Consider a multivariate data set of p-bands with grey levels

$$Z_i(x), i = 1,2,\ldots,p \tag{1}$$

where x gives the coordinates of the sample. If it is assumed that

$$Z(x) = S(x) + N(x) \tag{2}$$

where $Z^T(x) = \{Z_1(x), Z_2(x),\ldots, Z_p(x)\}$, $S(x)$ and $N(x)$ are the uncorrelated signal and noise component of $Z(x)$. Thus

$$Cov\{Z(x)\} = \Sigma = \Sigma_S + \Sigma_N \tag{3}$$

where Σ_S and Σ_N are the covariance matrices of $S(x)$ and $N(x)$, respectively. This noise is assumed to be additive but this technique can be applied to multiplicative noise by first taking logarithms of the observations.

The noise fraction of the i^{th} band can be defined as:

$$Var\{N_i(x)\}/Var\{Z_i(x)\} \tag{4}$$

the ratio of the noise variance to the total variance for that band. The maximum noise fraction can be defined as the linear transformations:

$$Y_i(x) = a_i^T Z(x), i = 1,\ldots,p \tag{5}$$

such that the signal-to-noise ratio for $Y_i(x)$ is maximum among all linear transformations orthogonal to $Y_j(x), j = 1,\ldots,i$. Furthermore it is assumed that eigenvectors a_i are normalized so that:

$$a_i^T \Sigma a_i = 1, i = 1,\ldots,p \tag{6}$$

Using arguments similar to those used in the derivation of principal components, it can be shown that the vectors a_i are the left-hand eigen-vectors of $\Sigma_N \Sigma^{-1}$, and that μ_i, the eigen-value corresponding to a_i, equals the noise fraction in $Y_i(x)$. Hence, from the definition of the MNF transform, MNF components will show steadily increasing image quality, with increasing component number. An important property of the MNF transform, which is not shared by principal components, is that - because it depends on signal-to-noise ratios - it is invariant under scale changes to any feature. Another useful property is that, it orthogonalizes $S(x)$ and $N(x)$, as well as $Z(x)$. The central problem in the calculation of the MNF transformation is the estimation of the noise component with the purpose of generation a covariance matrix that approximates Σ_N.

A number of methods to calculate the noise covariance matrix are suggested in the literature (Olsen, 1993). These are as follows:

1. Simple differencing. The noise is estimated as the difference between the current and neighboring pixel.

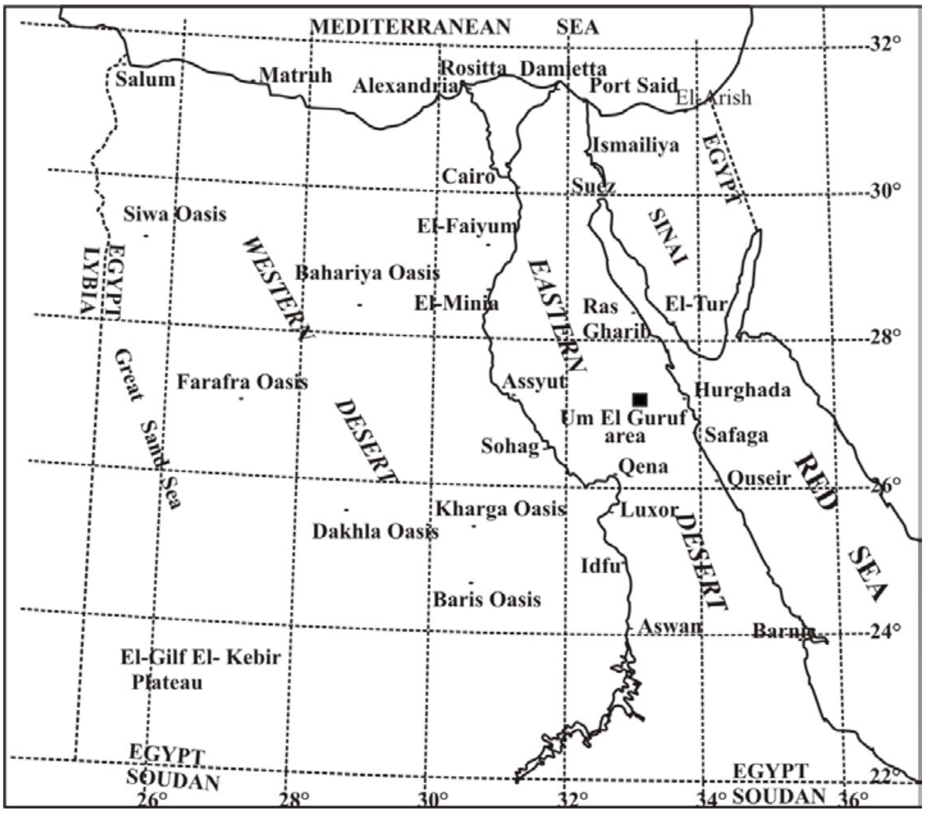

Fig. (1): Location map of Um El-Guruf area, north eastern desert, Egypt.

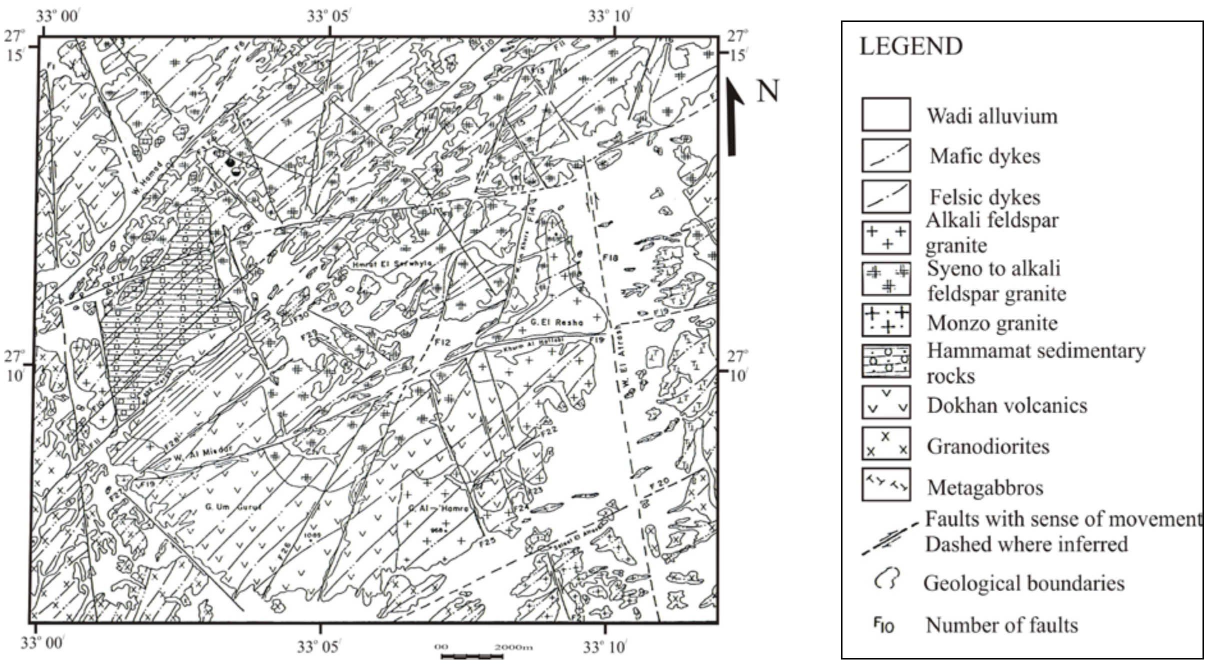

Fig. (2): Photo-Geological map of G. El Resha, Wadi El Atrash area (Abdel-Baset, 2006).

2. Differencing with the local mean. More pixels could be entered to the estimation by differencing between the current pixel and the local mean of a window.
3. The noise is estimated as the residual in simultaneous autoregressive (SAR) model involving the neighboring pixel to the W, NW, N and NE of the current pixel.
4. Differencing with local median. To avoid the blurring of edges and other details, the local median could be used instead of the local mean as in (2).
5. Quadratic surface. The noise is estimated as the residual from a fitted quadratic surface in a neighborhood.

Location of the studied area:

Gabal Um El-Guruf area is located in the North Eastern Desert and bounded by latitudes from 27º 06′ 00″N to 27º 15′ 00″N and longitudes from 33 º 00′ 00″E and 33º 11′ 30″E. The area is cut by four main Wadis; the NNW-SSE extending Wadi El Atrash, the ENE-WSW extending W. Al Misdar and NE-SW extending W. Hamad and W. Abu Harba.

The study covers an area of about 414 Km², mainly occupied by the Neoproterozoic Pan-African basement rocks. The area is covered by Late Precambrian crystalline basement rocks of a relatively high and rugged topography. G. Um Guruf (1089 m.a.s.l.), G. Al Hamra (968 m.a.s.l.) and G. El-Resha (869 m.a.s.l.) represent the most pronounced peaks, occupying the central and southern parts of the area.

Geological setting:

The main rock types in the area according to field relations and petrographic studies are arranged from the older to the younger as: metagabbros, older granites, dokhan volcanics, hammamat sediments, younger granites and the post granitic dykes (Abd el-Baset, 2006). The metagabbros are of limited distribution and occur as small low masses at Wadi El Atrash, in the eastern part of the area. They are highly deformed and severely altered.

The dokhan volcanics are generally composed of lava flows and pyroclastics. The lava flows are represented by intermediate (porphyritic andesite, trachy andesite and basaltic andesite) and acidic volcanics (rhyodacite and dacite). The associated pyroclastics are represented by andesitic and rhyodacitic lithic crystal tuffs, andesitic agglomerates and welded tuffs, ignimbrites.

The Hammamat sedimentary rocks are mainly exposed along the western part of the area unconformably overlying the dokhan volcanics at W. Abu Harba. There is a sharp intrusive contact between the younger granites and the small exposed Hammamat bodies along W. Hamad. The succession of the Hammamat sedimentary rocks consists of green to greyish green bedded conglomerates series (at the base), conglomeratic breccias, greywackes, sandstone, siltstone and some bands of purple slates interbedded with dark grey siltstones and sandstones.

The older granites are mainly granodiorites which are exposed as low hills in the southern and southwestern parts of the area. They are highly jointed and exfoliated, coarse grained mesocratic of light grey to greenish grey colour.

The younger granites are the main rock type exposed in the area, represented by Salaat El Atrash, Humrat El Sorwhyia, El Resha and Al Hamra plutons.

The post granite dykes in the area are of variable attitudes, dimensions and compositions cutting all the exposed rock units in the area. They are felsic dykes (including granite porphyry, granophyre, rhyolite and dacite) and mafic dykes, including andesite, dolerite and basalt. The dykes are trending NE-SW, ENE-WSW and N-S.

Applying MNF on the selected area:

The minimum noise fraction (MNF) transformation was used to show variation between bands in an image. This is a statistical method, which works out the differences in an image, based on the pixel DNs in various bands by using the eigenvectors and the eigenvalues to extract the principal vectors and directions of the data cloud.

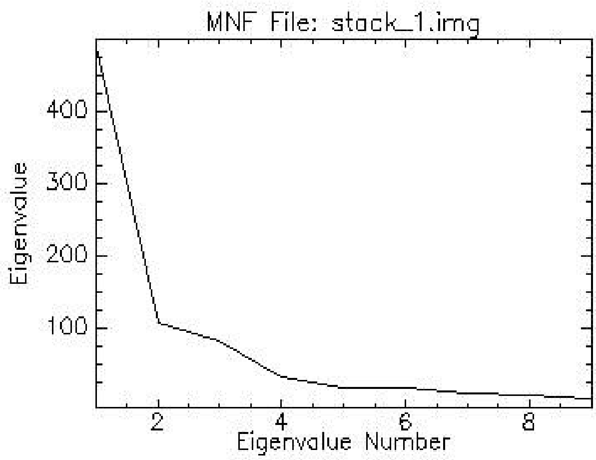

Fig. (3): The MNF eigen-values of the 9 eigen-images for the Aster data.

Band	Eigen-Values	Eigen-Values%	Cumu-lative%
1	789.576990	89.152%	89.152%
2	37.917930	4.281%	93.433%
3	27.236870	3.075%	96.500%
4	11.160375	1.260%	97.768%
5	7.441645	0.840%	98.608%
6	4.156868	0.470%	99.078%
7	3.518974	0.400%	99.478%
8	2.852718	0.322%	99.800%
9	1.789196	0.200%	100.00%

Figure 3 shows the amount of variation in each Minimum Noise Fraction (MNF) factor. The figure indicates that most of the variation is recorded in the

MNF (band 1), while the smaller amount of the variation is recorded in band 2, then in band 3 and so on until the line becomes nearly flat in band 9. The last MNF band (band 9) will be mainly noisy. It is noticed that up to 96.5% of the total variations in the data are gathered in the first three MNF factors.

Figure 4 shows the segregation of the signal to noise ratio (SNR) along the MNF components.

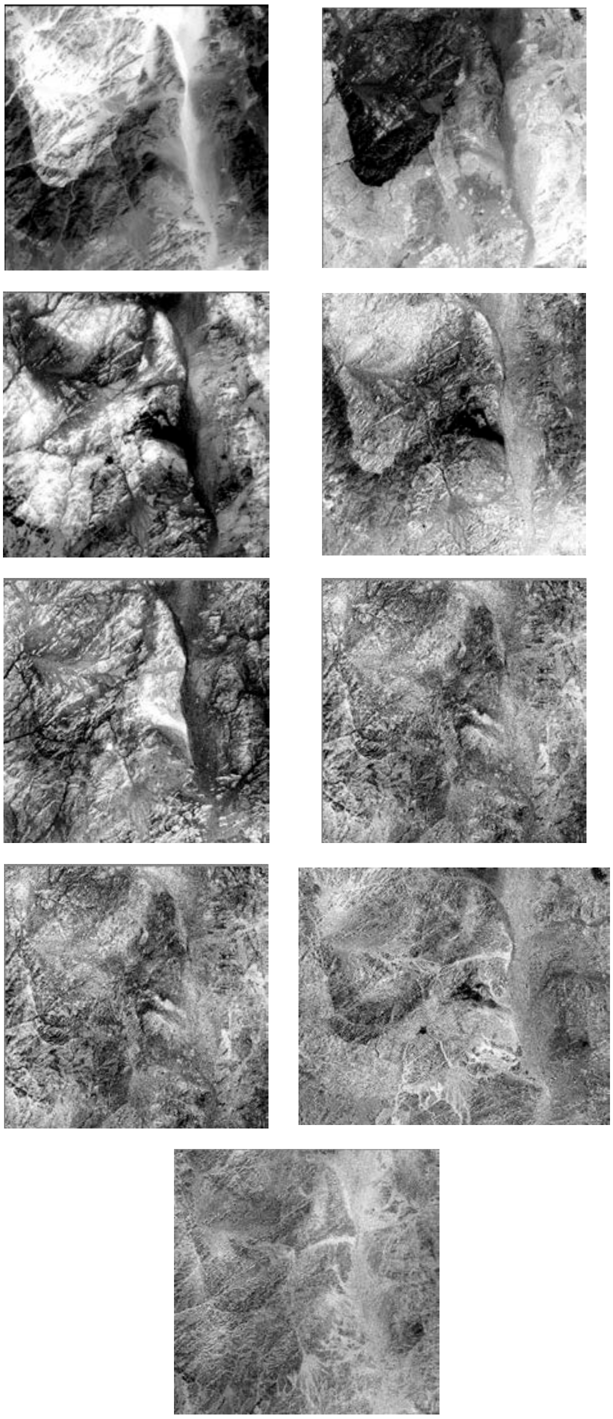

Fig. (4): Panel shows the segregation of signal to noise ratio along the MNF components. Left to right, top to bottom: MNF1 to MNF9 of the studied area.

Figure 5 shows a thematic mapping of the studied area due to the association of the 1, 4 and 9 bands without applying the MNF technique.

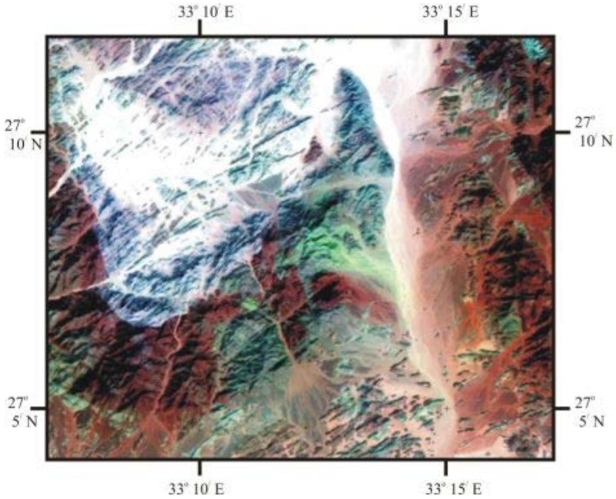

Fig. (5): False color composite image of bands 1, 4, 9 in RGB of the studied area.

Figure 6 shows a thematic mapping of the area according to the association of the first three MNF bands with the fundamental colors (Red-MNF1; Green-MNF2; Blue-MNF3).

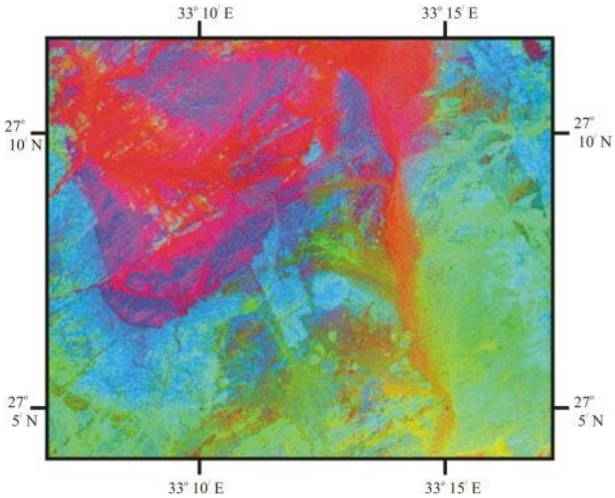

Fig. (6): False color composite image of 3MNFs in RGB of the studied area.

Our choice should then achieve the desired optimal ordering in terms of image quality.

CONCLUSION

The main purpose of this work is to apply the minimum noise fraction (MNF) method on the Satellite images of Gabal Um El-Guruf area in the North eastern Desert of Egypt in order to remove its noise which enhances image quality. The main characteristic of the MNF transform is that it orders the component images based on image quality by measuring the SNR. Therefore, it is invariant to scale changes, in any band, because it depends on the SNR instead of variance, like PCA, to order the component images .The MNF transformation used in this paper has the ability to provide an optimal ordering of images in terms of image quality. The MNF transform has the appealing property of sorting its components in descending order of SNR according to image quality, thus it tunes the amount of noise in the reconstructed data by setting a definite threshold. In general terms, the use of MNF sorts original data in a new order where features marked by low SNR are confined in few bands. The MNF performs better elimination of the stripping compared to the PCA, because the fewer retained components in the PCA inverse transform may result in missing useful information. The MNF performs better than PCA, because more components can be kept when severe stripping exists.

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