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# COMBINING NOISE-ADJUSTED PRINCIPAL COMPONENTS TRANSFORM AND MEDIAN FILTER TECHNIQUES FOR DENOISING MODIS TEMPORAL SIGNATURES

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**ABSTRACT.** Consistent multi-temporal images are necessary for accurate landscape change detection and temporal signatures analysis. Orbital images have a difficulty to maintain a temporal information precision due to several interferences that generate missing data. In this paper is developed a program in $C^{++}$ language for denoising MODIS temporal signatures considering two-phase scheme for removing impulse and white noise. In the first phase, the median filter is used to identify impulse noise. In the second phase, the Noise-Adjusted Principal Components (NAPC) transform is applied to eliminate white noise. Because they are two complementary methods, there is high performance in removing noise. The restored NDVI (Normalized Difference Vegetation Index) signatures showed a significant improvement providing a time series dataset that can be used to identify and classify the vegetation physiognomic types.

**Keywords**: NDVI temporal signature, MODIS, digital image processing, noise, MNF.

**RESUMO.** Imagens multitemporais consistentes são necessárias para uma acurada detecção de mudança e análise de assinaturas temporais. Imagens orbitais apresentam dificuldades para manter a precisão das informações temporais devido a várias interferências que geram perda de dados. Neste trabalho é desenvolvido um programa na linguagem $C^{++}$ considerando duas etapas para a remoção do ruído de impulso e branco. Na primeira etapa, um filtro de mediana é usado para identificar o ruído de impulso. Na segunda etapa, a transformação NAPC (*Noise-Adjusted Principal Components*) é aplicada para eliminar o ruído branco. Por serem os dois métodos complementares observa-se um alto desempenho na remoção de ruído. As assinaturas temporais NDVI (*Normalized Difference Vegetation Index*) restauradas mostraram uma melhoria significativa, fornecendo um conjunto de dados de séries temporais que podem ser usadas para identificar e classificar os tipos fisionômicos da vegetação.

**Palavras-chave**: assinatura temporal NDVI, MODIS, processamento digital de imagem, ruído, MNF.

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## INTRODUCTION

Images acquired on the same area at different times represent a valuable source of information for a regular monitoring of the Earth's surface that enables to describe the land-cover evolution, vegetation phenology, hazard events, human-induced changes, among others. Thus, a large number of multitemporal techniques using images have been developed during the last years. These techniques differ widely in refinement, robustness and complexity. There are two types of temporal remote sensing data commonly employed in large-scale vegetation studies: (a) discrete snapshots of the same region over time to analyze spatial changes in land cover; and (b) continuous time series of optical measurements to infer trends and dynamics of vegetation phenology (Asner, 2004).

The continuous time series of Normalized Difference Vegetation Index (NDVI) images are most applied in climate and phenological studies. Several time series analysis have demonstrated strong relationships between NDVI temporal signature and precipitation for different geographic areas and ecosystems (Nicholson et al., 1990; Grist et al., 1997). Other studies have used temporal signatures to classify the vegetation based on observation phenological patterns (Reed et al., 1994).

Then a consistent data acquisition interval among multitemporal images is necessary to accurate temporal-series signatures. However temporal precision in orbital images is difficult to be maintained due to different factors: atmosphere interferences (aerosols, clouds and shadows effects), bidirectional reflectance distribution factors, radiometric variation (sensor oscillation, solar illumination angle, among others) or noises, common features in remote sensing images (Hall et al., 1991; Du et al., 2001; Latorre et al., 2007). These effects cause serious problems for different applications like detection. For this reason, it is necessary for a perfect multitemporal analysis to remove these noises, clouds and their shadows effects (Cihlar et al., 1997).

This paper aims to develop a noise elimination method of temporal signatures combining the Median Filter and Minimum Noise Fraction (MNF) techniques. This work evaluates the NDVI MODIS time series over Cerrado vegetation types.

## STUDY AREA

Savannas represent a significant global biome covering a vast area of the African, American, Australian and Asian continents. The vegetation of savannas can be described as discontinuous upper layer of trees above a continuous layer of grasses. In Central Brazil a complex of neotropical savannas is locally known as "Cerrado". The strong seasonal distribution of rainfall combined with dystrophic soils with high Al and Fe contents as well as fire occurrence determined a wide range of adaptive, phenological strategies and biodiversity of these ecosystems (Sarmiento, 1984).

The Cerrado has a typical phenology, with a high dependence in availability of nutrients and water, associated to the seasonal climate, water table depth and fire (Coutinho, 1990). Thus, the savanna region of the Central Brazil shows vegetation patterns attributed for underlying variations in soils and soil-moisture of different geomorphology and lithology. According to the Köeppen classification the climate in Cerrado domain is Aw type and dry winters and rainy summers characterize it. Average precipitation is 1600 mm, mostly concentrated in the wet season (from October to March) (Adámoli et al., 1987).

The Cerrado biome has special ecological conditions where savanna vegetation is predominant, interspersed with riparian forests, patches of semideciduous forest, swamp and/or marshes. The "Cerrado Sensu Lato" includes physiognomies varying as "Campo Limpo" (a grassland type), through "Campo Sujo", "Campo Cerrado", and "Cerrado Sensu Stricto" (savannic intermediary formations), to "Cerradão" (a forest type). The principal characteristic for differentiation is the density of woody individuals (trees and shrubs) (Goodland, 1971; Ruggiero et al., 2002).

Moreover, the land cover dynamics in these vegetation types show an intensification of agriculture systems, wood extraction and land degradation processes. The peculiar physical conditions and severe historical anthropogenic pressure have caused extensive natural vegetation losses, increasing soil erosion, burned area and biological diversity reduction. Thus, the lack of appropriate public policies in the land management compromises the environmental condition.

Brasília National Park was created in 1961 with approximately 30,000 hectares located between 15°34″S and 15°48″S of latitude and 47°52″W and 48°06″W of longitude coordinates (Fig. 1). Soils are usually well drained, strongly acidic, dystrophic (Oxisols) and with high Al and Fe contents (Haridasan, 2001). In the Brasília National Park there are the riparian forest, cerrado and grassland.

## MATERIAL AND METHODOLOGY

### MODIS Data

The Moderate Resolution Imaging Spectroradiometer (MODIS) is an Earth Observing System (EOS) sensor designed to measure daily biological and physical processes in global scale in order to understand the dynamics and processes occurring on the Earth's surface and in the lower atmosphere (Huete et al., 2002). The first sensor was mounted on NASA's Terra platform, which was

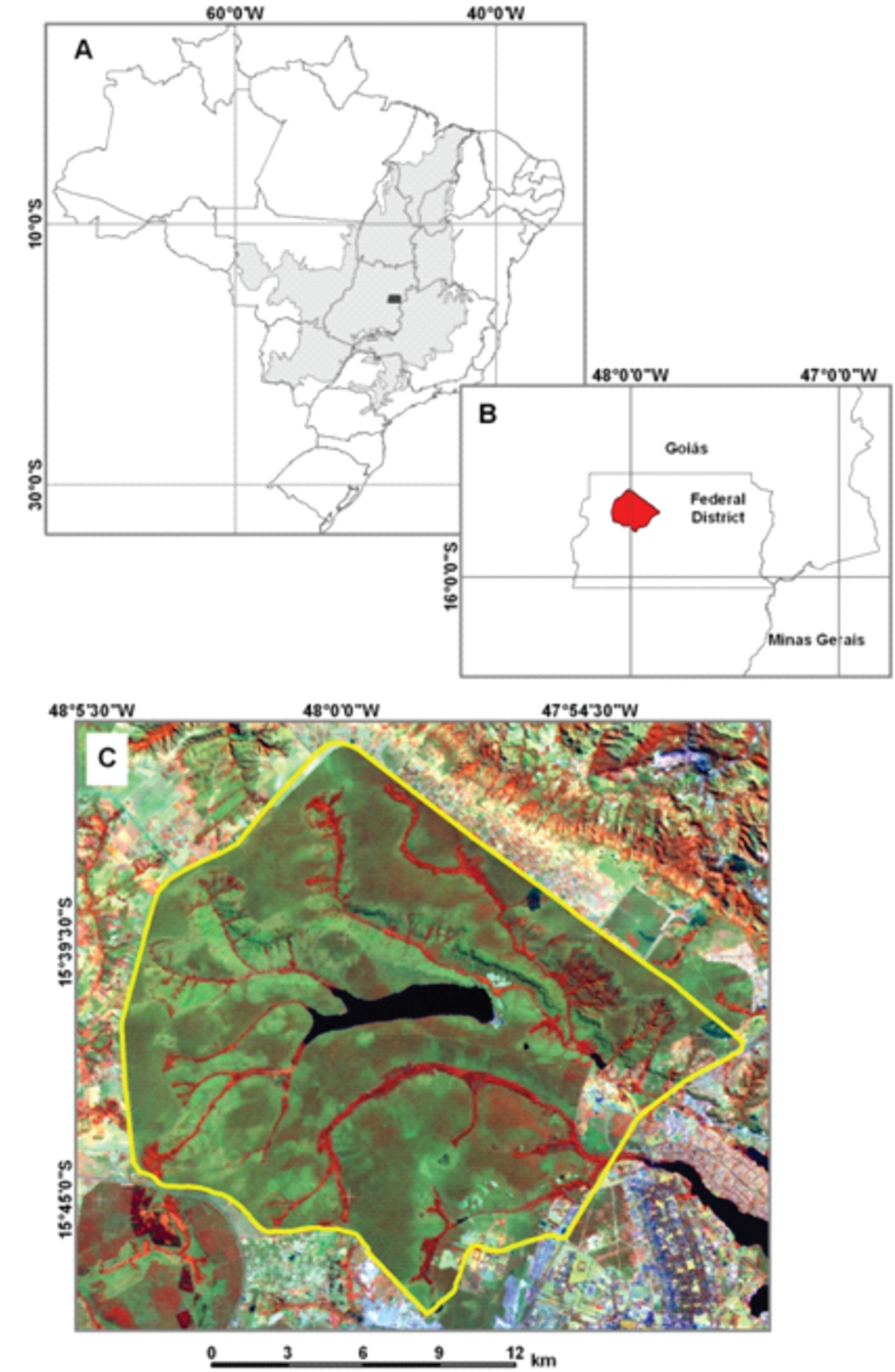


**Figure 1** – Brasília National Park localized 10 km far from Brasília downtown, in the Federal District, in central Brazil.

launched on December 18, 1999 and began to provide MODIS products since 2000. The second sensor was launched on May 4, 2002 onboard the NASA's Aqua platform.

Beyond the spectral bands, MODIS Science Team developed data products using specific algorithms planned for EOS/MODIS to supply the needs of global change research (Justice et al., 1998). In this work we used the NDVI products, important tool for monitoring of the Earth's vegetation. The normalized difference vegetation index (NDVI) is characterized to be sensitive to chlorophyll content. Thus, the MODIS VI product has offered a time series for a precise monitoring of the seasonal, interannual and long-term variations of vegetation phenological and biophysical parameters. For this study the NDVI images were acquired along 2000-2006 time period with 250-m spatial resolution and 16-day composite interval data.

## Elaboration of Images Cube Composed by NDVI Temporal Series

Representation of this NDVI set can be obtained by building the cube of temporal series images (Carvalho Júnior et al., 2006, 2008, 2009; Santana et al., 2010). The cube is formed by co-registered multitemporal images with its three dimensions: $x$, $y$ and $z$ (temporal NDVI profile) acquired in the same geographical area at different times. The header file of the multitemporal images must contain its respective geographical coordinates and acquisition dates. Figure 2 shows a cube image with the temporal spectrum in a perspective view.

## Median Filter

Noise is very common in multitemporal images and hinders the identification and quantification of targets. Consequently, the noise elimination is necessary to acquire a high-quality spectrum. For this purpose, the present paper applies the combination of the two techniques Median Filter and Minimum Noise Fraction (MNF) for eliminating image noises.

Turkey (1977) introduced the median filter operation in signal processing. The method became one of most popular and simple digital technique used for signal smoothing and entropy reduction, because of its good denoising power (Astola & Kuosmanen, 1997) and computational efficiency (Huang et al., 1979). This nonlinear smoothing technique is known for preserving signal edges or monotonic changes in trend and for being particularly effective in removing impulse noise of short duration that cannot be achieved with linear algorithms (Ataman et al., 1981). An impulse noise is composed by fewer points whose values are different from the surrounding regions. Thus, in these respects, the median smoother is better than the linear filter. Median filters have been applied to various types of data and have achieved some very interesting results in areas of digital signal processing, which include image enhancement (Pratt, 2007) and speech processing (Rabiner et al., 1975).

The median is a particular case of the $i^{th}$ order statistic (or rank statistic) of a finite set of real numbers. The median filter performs a window moving over temporal signature and obtains the median value that is taken as the output. Arranging all the observations from lowest to highest value, the median value of a window is the middle one. Considering an order statistic of $N$ real numbers $(x(i)\ldots, x(N))$, where $N$ is window digital filter, the minimum is then $x(1)$, the maximum $x(N)$, and the median $X((N+1)/2)$. Thus, the implementation of a median filter requires a very simple digital nonlinear operation.

Normally in the majority of noise cases, a median filter of length $N = 3$ completely eliminates all impulse. However, when the cloud and shadow are present simultaneously in successive images, the median filters cannot eliminate impulse noise completely, i.e., the expected value of the impulse amplitude at the output is not zero. For this case a larger windows filter can be used.

However the median filter presents difficulty to eliminating non-constant signal structures, such as the white noise. Kuhlman & Wise (1981) investigated the output spectrum of a median filter for white noise input points with several different distributions. These authors found that the spectral shape of output is virtually independent of the input distribution. Nodes & Gallagher Jr. (1984) observed that the average filter is better than the median filter for eliminating the Gaussian noise. But, when impulse or double exponential noise is present, the median filter is better than the average filter. This is due to the ability of the median filter to eliminate low probability high power impulses, which cannot be done with linear systems.

A specific median filter module for time series image processing was developed in $C^{++}$ language. In this program, the User establishes a NDVI time series cube. For an accurate filtering it is required a continuous time series with a same time interval.

## Minimum Noise Fraction (MNF) and Noise-Adjusted Principal Components (NAPC)

Initially the Minimum Noise Fraction (MNF) and Noise-Adjusted Principal Components (NAPC) were developed for hyperspectral image processing. However, these methods are also adequate to eliminate noise interferences of larger amount of data, such as aerial gamma-ray survey (Dickson & Taylor, 1988).

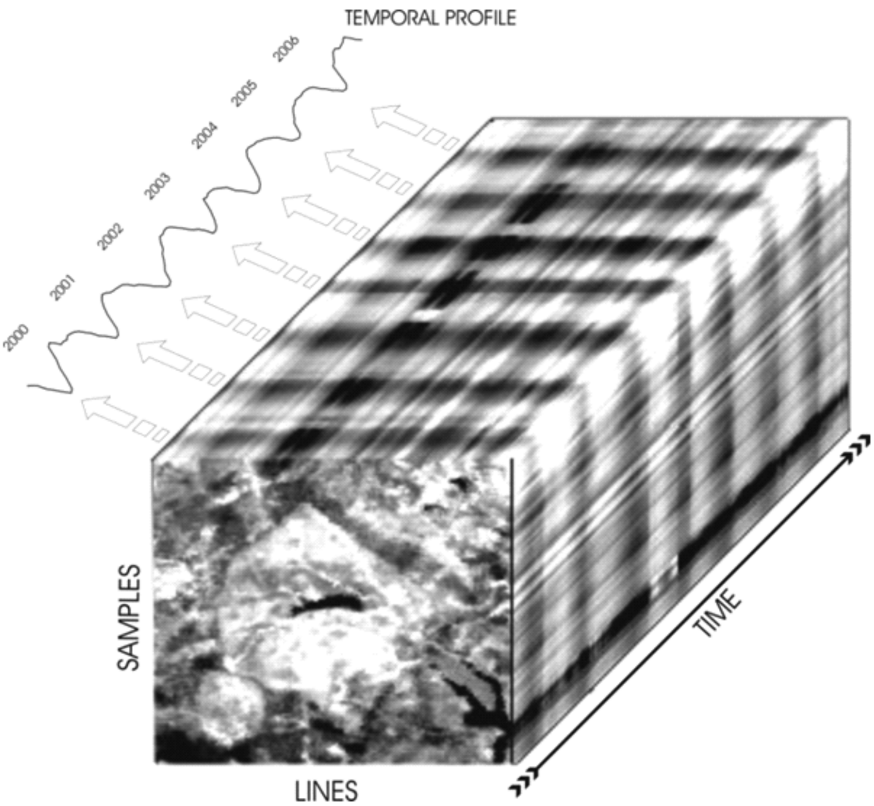


**Figure 2** – The concept of NDVI time series cube is shown, where a temporal spectrum can be measured for each spatial element in an image.

MNF is a transformation similar to Principal Component Analysis (PCA) (Green et al., 1988). PCA transformation can be divided into three steps (Richards, 1984):

(a) Derivation of the variance-covariance matrix $(VCM)$ for $N$-band of the time series data;

(b) Computation of orthonormalized eigenvectors of $VCM$, denoted by $U$, and of its eigenvalues, represented by $A$; and

(c) Linear transformation of the data set $(x)$ for the principal components $(Z)$ from the equation $Z = U^T(x - m)$, where $m$ is the mean of the pixels for each band.

The MNF transform adopts similar arguments to derivate its components. This method is a linear transformation that maximizes the signal-to-noise ratio to order images, considering, therefore, the image quality (Green et al., 1988). The MNF can be subdivided into four stages (Fig. 3):

(a) Acquisition of a noise sample and calculation of the variance-covariance matrix of the noise $(VCM_N)$;

(b) Calculation of the noise fraction index $(NFI)$, by multiplying the variance-covariance matrix of the noise $(VCM_N)$ and the inverse variance-covariance matrix of the data set $(VCM^{-1})$, so $NFI = VCM_N * VCM^{-1}$;

(c) From $NFI$ compute its orthonormalized eigenvectors $(K)$ and implement a linear transformation function $Z = KT(x - m)$, where $x$ is the individual pixel and $m$ is the mean of the pixels for each band; and

(d) MNF inversion considering only signal information. Subsequent retransformation results in cleaned images and spectrum with little signal loss.

Therefore, the MNF calculates a noise fraction index $(NFI)$, instead of PCA, which uses a variance-covariance matrix of the data set $(VCM)$. Consequently, the MNF components will show steadily increasing image quality, unlike the usual ordering of principal components.

NAPC transform is mathematically equivalent to MNF transform, but the former transform can be implemented using standard principal components algorithm, without the need for matrix inversion and eigenanalysis of a nonsymmetric matrix (Lee et al., 1990). NAPC transform consists of a sequence of two-cascaded

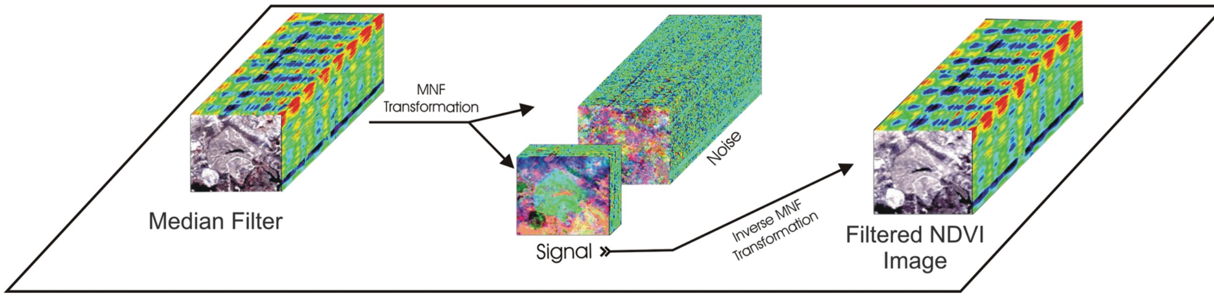


**Figure 3** – MNF transformation procedures in the temporal NDVI cube. The NDVI filtered cube can be converted in MNF space, where the signal is separated from noise. The subsequent retransformation from signal set results in cleaned images and spectrum with little signal loss.

principal component transforms: noise and transformed data set. In detail, the NAPC transform consists of the following stages (Roger, 1994):

(a) From $VCM_N$ compute its orthonormalized eigenvector matrix $(E_n)$ and the diagonal matrix of its eigenvalues $(A_n)$, then $E_n^T VCM_N E = A_n$;

(b) Construct a renormalization matrix $F = EA_n^{-1/2}$, for which $F^T VCM_N F = I$ and $F^T F = A_n^{-1/2}$, where $I$ is the identity matrix;

(c) Transform the data covariance matrix $(VCM)$ by $F$ to give the noise-adjusted data covariance matrix, $VCM_{adj} = F^T VCMF$;

(d) From $VCM_{adj}$, compute its eigenvector matrix $(G)$; and

(e) Linear transformation of the dataset $(x)$ for the NAPC components $(Z)$ by following equation $Z = HT(x - m)$, where $H$ is described by $H = FG = EA_n^{-1/2}G$.

The application of NAPC transform requires knowledge of the noise covariance matrix of the data. Thus, the key problem is to find out which kind of noise we want to eliminate (Carvalho Júnior et al., 2002). The noise reference can be obtained from externally or internally of the images.

External noise reference is obtained from the dark references during the flight and used to evaluate the instrumental noise. This procedure is not applied for time series images being adequate for multispectral and hyperspectral images.

Internal noise reference is obtained from the images by using the statistic techniques that enables to discriminate noise fraction from signal. Maximum Autocorrelation Factor (MAF) can be used to this purpose (Switzer & Green, 1984). Spatial covariance $(VCM_D)$ is defined as the covariance matrix between the original image, represented by $I(x)$, and the same image $I(x + D)$ shifted by an mount $D$. The noise covariance matrix $(VCM_N)$ can be to estimate using the following equation:

$$VCM_N = 1/2VCM_D \tag{1}$$

where

$$VCM_D = (I(x) - I(x + D))(I(x) - I(x + D))^{-1} \tag{2}$$

In this algorithm was used a $D$ equal to 1. The $VCM_D$ can be calculated considering shifts from one of eight neighbor directions or by the average of two to eight directions given by the User, according to Equation (3).

$$VCM_D = MVCM = (\Sigma VCM_i)/n \tag{3}$$

where, $MVCM$ is an average spatial covariance of directions selected; $i$ is the direction of nearest neighbors (1-8); and $n$ is the number of the direction chosen by the User. Thus, the $VCM_D$ matrix is obtained and applied in the steps of the NAPC transform.

However, noise removal is only performed with the inversing $NAPC$ transform. During the inversion is necessary to eliminate noisy bands using only signal bands. This procedure reduces noise in the original data space. For the inversion operation is need to use as input both $NAPC$ images as statistical file containing the mean of the original bands $(M)$ and matrix $H^T$. Smoothed images $(SI)$ are obtained by the following expression:

$$SI_i = NAPC_i(H^T)^{-1} + M_i \tag{4}$$

In order to apply MNF method, it is necessary to separate noise in three types, according to its variance and correlation characteristics: (a) uncorrelated noise with equal variance in all bands (white noise), (b) high correlation noise, and (c) noise with structure of unknown covariance.

The uncorrelated noise presents a spherical distribution around the data mean. In this case, MNF provides an optimal ordering of image quality and its elimination. The existence of high correlation noise as a $Yi(x)$ function allows the concentration of noise in a single MNF component.

However, MNF from two-cascaded principal component transformation is not efficient for elimination of noise with unknown covariance structure, such as cloud and shadow. This noise is confined into a single band, although it can be extended for two or three channels. Complementarily the median filter is extremely efficient in this noise elimination.

## RESULTS

### Software

Specific software for denoising MODIS temporal signatures were developed in $C^{++}$ language. The program has the following modules: (a) median filter, (b) NAPC transform, and (c) Inverse NAPC transform. In this program and the User establishes an images set at different times. The procedure requires input images the following characteristics: (a) co-registered multitemporal images with its three dimensions $x$, $y$ and $z$ (reflectance profile); (b) resized images with the same dimension (line and column); and (c) preferably images with radiometric normalization that minimizes radiometric differences among multitemporal spectra caused by inconsistencies of acquisition conditions rather than changes in surface reflectance.

In median filter module, the User defines the temporal images and the window size. The result obtained by filtering is again processed by MNF transformation. As input in MNF transformation is requesting the temporal image and the selection of directions used in the MAF calculation. Considering a window size $3\times3$ pixels the User can choose from the surrounding central pixel the directions that will be used to estimate the spatial covariance ($VCM_D$) by pressing the directional buttons (Fig. 4). Therefore, the autocorrelation estimation adopts 1 pixel as distance. The $VCM_D$ is calculated considering the average of directions chosen.

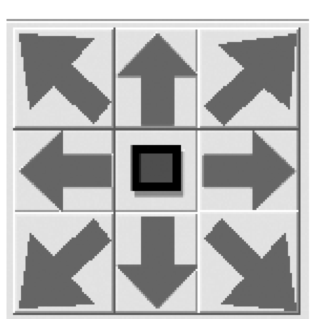

**Figure 4** – User interface containing the directions window for the spatial covariance calculation.

The final processing required is inverse MNF transform, which uses as input the images and statistical data generated by MNF transformation. This procedure involves noisy elimination of the MNF bands in order to reduce noise in the original data space. The selection process of band signal can be done interactively, where the User before performing the inversion can see the result for a spectrum image.

### Noise Removal

The sequential procedures of the median filter and MNF transform enabled to eliminate different kinds of noise from the time series.

The first stage of the median filter is performed to segregate isolated noises originated by cloud, shadow and instruments. In NDVI spectra, the median filter keeps undisturbed the constant neighborhoods and edges, while eliminates isolated noise.

Edges are abrupt changes where the set of points that increase or decrease surrounded on both sides by constant neighborhoods. In NDVI spectrum of the natural vegetation, the edges do not appear prominence, only when there are burning events or anthropic alterations. Normally the vegetation time series present a sinusoidal pattern with gradual variation from composition ratio between nonphotosynthetic vegetation (NPV) and photosynthetic vegetation (PV) along the year.

The filtering over isolated noise induces occasional formation of the narrow plateau composed by two points consecutive with same values. Rarely, the evidence of remained noise given by noise predominance in window filter is noted. In this case a filter with larger size windows can be applied.

The second stage is the MNF transformation that is used to eliminate uncorrelated noise with equal variance in all bands as the narrow plateau. This transformation must be always used on bands free of impulse interference. The resulting spectra show a smoother form, with removal of the narrow plateau and remained noise (Fig. 5).

Thus, the combined techniques enabled to develop a fast and accurate method for multitemporal image correction. Besides, the method generates continuous spectra for each pixel.

The procedure is adequate not only in temporal signatures correction, but also in spatial correction by improving visual image quality. Despite the proposed method not acting in the spatial dimension, being restricted in temporal dimension, the results obtained in the present investigation also indicated important contribution in image correction (Fig. 6).

### Vegetation Signatures

All MODIS temporal vegetation signatures oscillate in an approximately sinusoidal pattern, for the period of one-year (Fig. 7). These interannual cycles of greenness correlate with vegetation phenological cycle and large-scale precipitation patterns. The NDVI signatures of the vegetation types present a high linear cor-

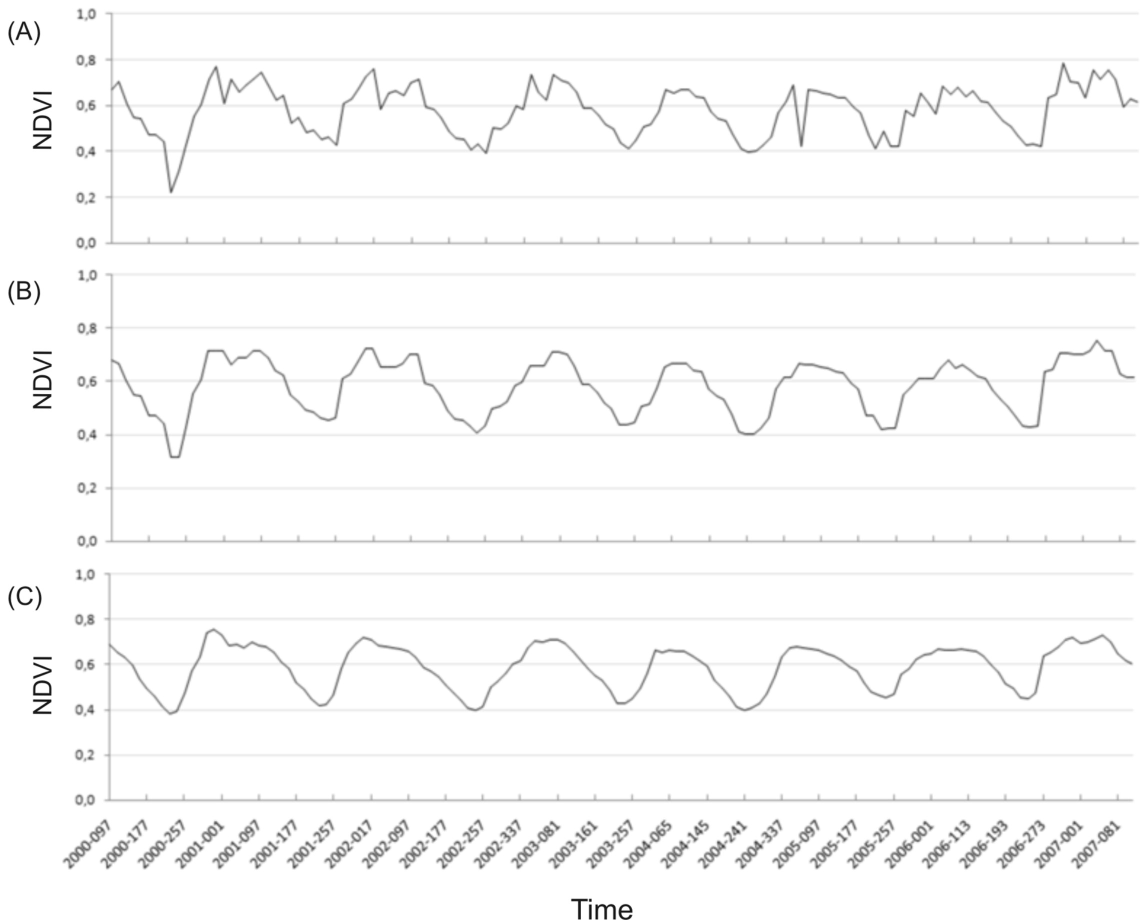


**Figure 5** – Spectra results of different stages: (a) primary spectrum, (b) median filter with a window width of $3 \times 3$ pixels and (c) median filter plus MNF transform.

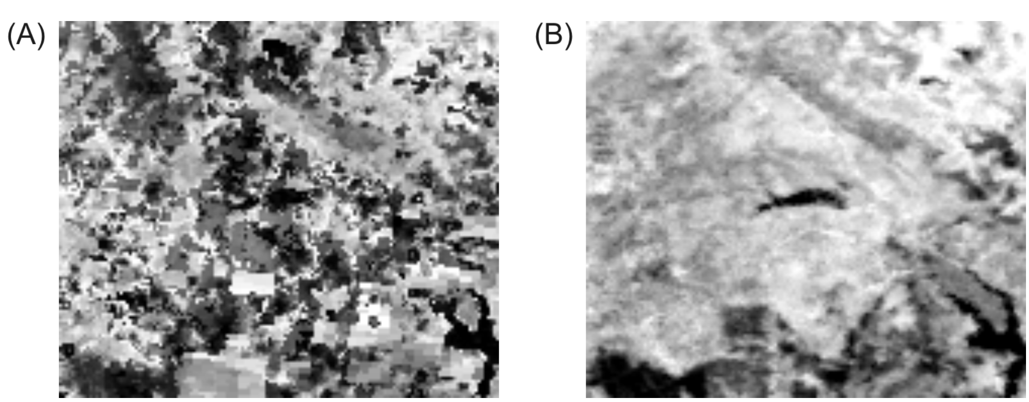


**Figure 6** – Two images of same date, one corresponding to the original image (a) and other the corrected image from the use of Median Filter and MNF combined transform (b). In this case, where there are extensive areas with noise, the use of the spatial filter does not get results as consistent as the temporal correction.

relation due to the similar sinusoidal pattern. The main differences among vegetation types are in the intensity and range values.

The Figure 7 shows the typical temporal signatures for the grassland, savanna and forest types. The NDVI signatures of the forest type present the highest values for every year. Moreover, the forest type describes the lowest ranges produced by subtraction between the maximum and minimum values. The grassland type shows a distinct behavior with lesser values and highest ranges.

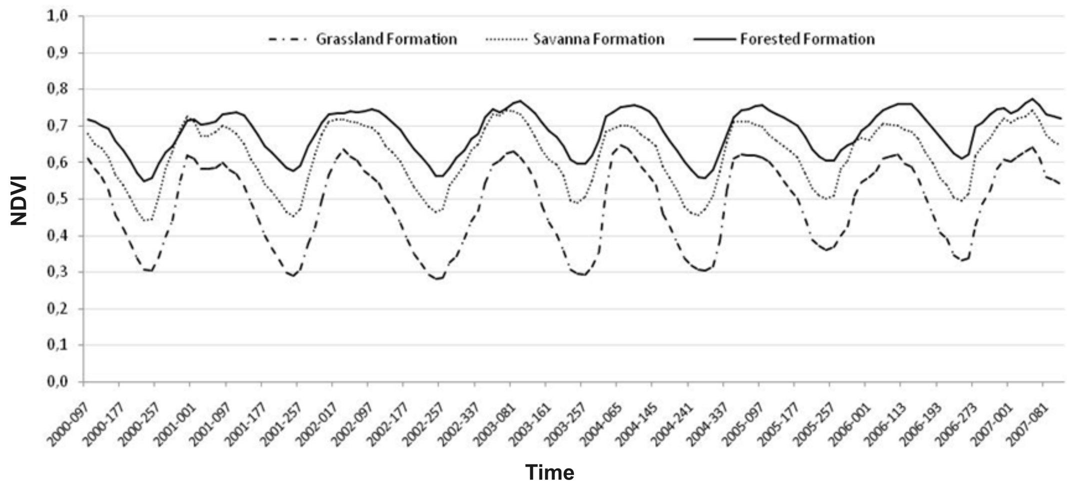


**Figure 7** – Typical temporal signatures for the grassland, savanna and forest types.

The savanna vegetation type presents an intermediary behavior between grassland and forest types. Thus, NDVI signatures appear to be very useful to discriminate among these vegetation classes. This will be subject for further research work.

## CONCLUSIONS

The sequential procedure of Median Filter and MNF enabled to eliminate different kinds of noise from the image. This procedure uses a continuous time series with same time interval. Median Filter segregates impulse noises and MNF transform considered the uncorrelated noises with equal variance in all bands and the high correlation noise. The combined techniques method enabled to reduce the noise by a smoothing process. Thus, the method provides the necessary information to support vegetation classification based on temporal signatures.

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