ENHANCEMENT AND SMOOTHING OF HYPERSPECTAL REMOTE SENSING DATA BY ADVANCED SCALE-SPACE FILTERING

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ABSTRACT. While hyperspectral data are very rich in information, their processing poses several challenges such as computational requirements, noise removal and relevant information extraction. In this paper, the application of advanced scale-space filtering to selected hyperspectral bands was investigated. In particular, a pre-processing tool, consisting of anisotropic diffusion and morphological leveling filtering, has been developed, aiming to an edge-preserving smoothing and simplification of hyperspectral data, procedures which are of fundamental importance during feature extraction and object detection. Two scale space parameters define the extent of image smoothing (anisotropic diffusion iterations) and image simplification (scale of morphological levelings). Experimental results demonstrated the effectiveness of the developed scale space filtering for the enhancement and smoothing of hyperspectral remote sensing data and their advantage against watershed over-segmentation problems and edge detection.

KEY WORDS: mathematical morphology, nonlinear filtering, anisotropic diffusion, segmentation, edge detection.

1. INTRODUCTION

Multispectral imaging sensors and imaging spectrometers have been significantly improved during the past decade. Hyperspectral imagery (HSI) is composed of multispectral images in many, very narrow, contiguous spectral bands throughout the visible, near IR, and mid IR portions of the spectrum. Nowadays, processing HSI leads to a wide variety of earth imagery applications including:

i) solutions to support forest inventory (Kyoto products) and forest chemistry, timber management applications, wildfire modeling (Gensuo et al., 2006; Peter and Lucas, 2006),

ii) other environmental applications such as agricultural, marine and natural resource exploration, land-use analysis, terrain categorization, material classification, change detection and wetlands monitoring (Debba et al., 2005; Ye et al., 2006; Enrica et al., 2006; Nguyen and Lee, 2006),

iii) civil government applications for pervious-impervious surface mapping, creation and maintenance of GIS data layers for roads and structures, identification of urban green space (Jouan and Allard, 2004; Vahtmäe et al., 2006),

iv) homeland security solutions for the creation and maintenance of GIS data layers, identification and mapping of high-value assets (pipelines, power plants, etc), monitoring of borders, and development of 3D urban models for preparing disaster and emergency services (Segl et al., 2003; Shrestha et al., 2005),

v) medical imaging such as tumors detection (Levenson and Mansfield, 2006; Martin et al., 2006),

vi) industrial applications in manufacturing processes for product quality assurance and quality control (Tatzer et al., 2005) and

vii) military applications such as automatic target recognition and tracking, including those targets that may employ camouflage, concealment, and deception (Zheng et al. 2003; Briottet et al., 2006).

Unfortunately, atmospheric scattering, secondary illumination, changing viewing angles, and sensor noise degrade the quality of HSI impeding the above application. It is normally found that the noise level in HSI is high as their narrow bandwidth can only capture very little energy that may be overcomed by the self-generated noise inside the sensors (Chaichoke, 2006). Additionally, physical disturbances such as the fluctuation of light illumination and atmospheric states make the situation worse as the disturbances decrease the precision of spectral signals recorded by the sensor.

Spectral smoothing techniques including both linear and non-linear methods are popularly used in a large number of modern hyperspectral remote sensing studies for removing noise from the spectral data (Andréfouët et al., 2003; Thenkabail et al., 2004; Chaichoke, 2006). However, most of these studies do not use any strict optimizing criteria to select suitable smoothing filters and in several cases in which linear filters are applied, smoothing cause changes to the original spectral data that could lead to incorrect results in subsequent analyses (Chaichoke, 2006).

For improving HSI automated feature extraction and data exploitation capabilities, advanced image enhancement, smoothing and simplification filtering have to be applied. Such applications are a vital pre-processing step in computer vision, remote sensing and photogrammetry feature extraction procedures (Argialas and Harlow 1990; Paragios et al., 2005; Karantzalos and Argialas, 2006).

In this paper, two advanced nonlinear scale space filtering methods Anisotropic Diffusion Filtering (ADF) and Morphological Levelings (ML) have been employed for the enhancement and smoothing of HSI. ADF and ML are nonlinear filtering operators with many interesting properties (Weickert 1999, Meyer and Maragos 2000). They can highlight the distinction between the features in an image so that on the one hand visual quality is improved and on the other hand they facilitate edge detection and segmentation techniques (Karantzalos and Argialas, 2006). Especially with the use of ML filtering, details vanish from one scale to the next but the contours of the remaining objects are preserved sharp and perfectly localized (Meyer and Maragos 2000). Hence, objects are enhanced so that edge detection or segmentation operators can detect accurately object boundaries.

2. METHODOLOGY

2.1 Anisotropic Diffusion Filtering and Morphological Levelling

To overcome the limitation of linear scale space (Gaussian smoothing inevitably blurs edges and other important features due to its isotropic and low-pass nature), two representations of nonlinear scale spaces have been proposed: one is based on anisotropic diffusion filtering and the other on mathematical morphology.

Among ADF equations (Weickert, 1999), the geometry-driven diffusion by Alvarez, Lions and Morel (ALM) (Alvarez et al., 1992) was emplyed here since it has already has been tested with promising results in Karantzalos and Argialas (2006), for edge detection and segmentation to panchromatic high resolution satellite imagery. This anisotropic process reduces the diffusivity at those locations that have a larger likelihood of being edges based on their larger gradients. If the gradient magnitude is small, then the diffusion is strong and if it is large at a certain pixel (x, y), this pixel is considered as an edge point, and the diffusion is weak.

The theory and implementations behind the nonlinear morphological scale-spaces considers the evolution of curves and surfaces as a function of their geometry. The basic ingredients of all standard multiscale morphological operators were dilations and erosions of increasing size. However, dilations and erosions by themselves cannot be used to represent the successive scales because they displace the image boundaries and this is a crucial matter in all geo-science feature extraction applications. A recent advancement to this displacement problem came from the development of a more general powerful class of self-dual morphological filters, the levelings. The levelings possess many useful algebraic scale-space properties, as explored in Meyer and Maragos (2000), which are best studied in a lattice framework.

2.2 Developed scheme for the enhancement and smoothing of HSI.

Enhancement and smoothing filtering was applied to a subset (3 bands) of the original HSI bands, after standard feature selection procedures. Feature selection, which is an operation of major importance for HSI, was carried out to identify band combinations with the highest spatial autocorrelation. This increases not only the accuracy of the spectral representation of the classes in the selected features, but also their spatial representation (Thenkabail et al., 2004; Chaichoke, 2006).

The developed processing scheme, which has been introduced as an advanced nonlinear scale space representation towards a superior image simplification and smoothing (Karantzalos and Argialas, 2006), was applied to each of the selected hyperspectral bands. The goal was to obtain the major advantages of each filtering, try to synthesize them and investigate the possibility for a much better filtering result. The developed scheme used as a reference image for ML the output image of the ADF. In this framework the ML was dominated by an already nicely enhanced and smoothed image in which edges and abrupt intensity changes have been respected. In all cases ADF was performed with a small number of iterations, since the goal was just to obtain a slightly smoothed version of the original image. With such a reference image the multiscale markers obtained from sampling its Gaussian scale-space, did not start blurring the original image but they started from blurring the ADF output. This theoretically was expected to yield a more edge preserving geometric driven image simplification.

3. RESULTS AND DISCUSSION

The developed scheme has been applied to a number of hyperspectral images which are available from the MINEO EU project (Data Set of hyperspectral airbone surveys, http://www2.brgm.fr/mineo/) and to ASTER Level 1 data. In figures 1 and 2 the application of the developed scheme to an image crop from the MINEO dataset in Finland, Boreal environment test site, is presented. The available image had been already reduced to three bands through a band selection procedure.

The aim was to evaluate the developed scheme as a pre-processing filtering tool for edge detection and image segmentation (more specifically for solving over-segmentation problems of the watershed transformation). Watershed segmentation is very sensitive to small variations of the image magnitude and consequently the number of generated regions is undesirably large. As it is demonstrated in figures 1 and 2 the developed filtering tool managed to decrease the original image's heterogeneity (in spectral and spatial domain) so that in the resulting segmentation adjacent pixels appeared more aggregated. This resulted to an over 40% decrease in the number of output segments. In figure 3, the developed filtering tool was applied to an ASTER Level 1 satellite image from the Death Valley region, USA.

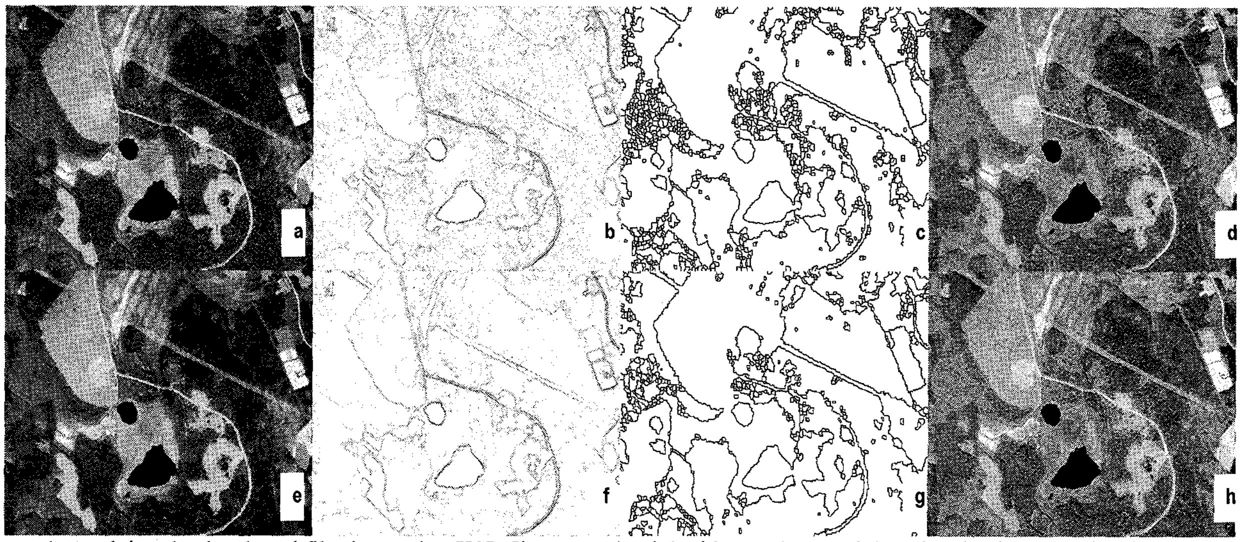

Figure 1. Applying the developed filtering tool to HSI. First row: a) original image (setected three bands), b)color edge detection to (a), c) watershed segmentation to (a) and d) watershed result superimposed to (a). Second row: e) smoothed image after the application of the ADF (40 iterations) and the ML (scale 3), f) color edge detection to (e), g) watershed segmentation to (e) and h) watershed result superimposed to (e).

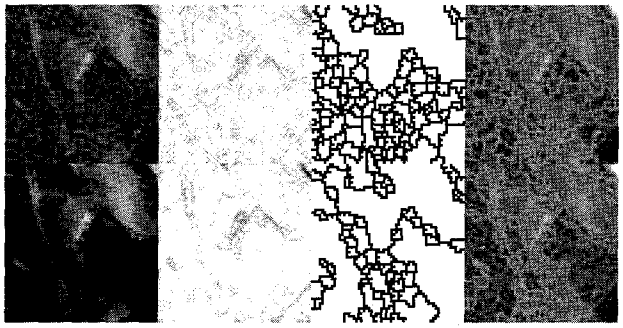

Figure 2. Zoom to an image crop of figure 1. All images follow the figure 1 order.

The developed filtering tool was applied to the three bands of ASTER data with a ground resolution of 15 meters. Again, the developed scheme by simplifying the image and removing irrelevant image structures deal with watershed over-segmentation problems, since not only enlarged but also created new flat (smooth) image zones. Segmentation quality was compared quantitatively in terms of the number of regions obtained after using the developed algorithm. Over a 10% decrease in the number of output segments was achieved.

Finally, after a close look in all figures, one can observe that the applied edge-preserving, geometric-driven filtering i) resulted into the preservation of the more prominent/ meaningful edges (second column) after the application of a color edge detection (Zenzo, 1986) and ii) forced the merging of pixels which belong to the same and not to irrelevant categories/objects (last column).

4. CONCLUSIONS & FUTURE PERSPECTIVES

Experimental results showed that the nonlinear scale space filtering can be applied to HSI with promising results for edge detection and segmentation tasks. These tasks are important during middle and high level computer vision feature extraction procedures. Finally, the developed scheme is currently under evaluation for its contribution to HSI band selection process.

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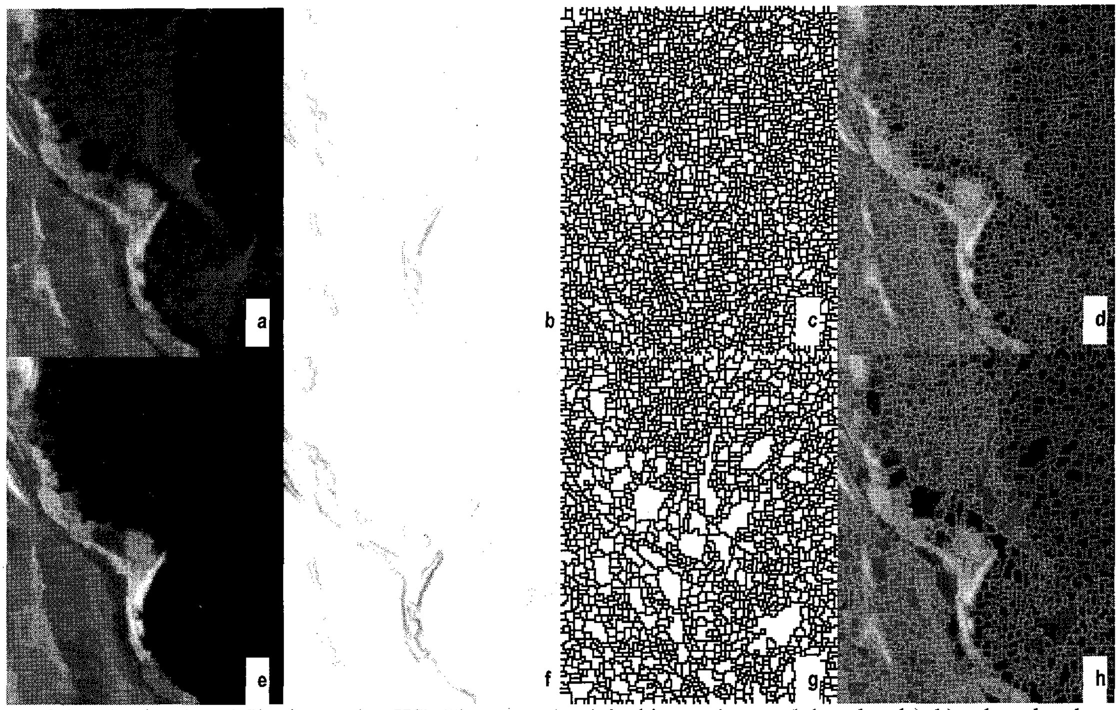

Figure 3. Applying the developed filtering tool to HSI. First row: a) original image (setected three bands), b) color edge detection to (a), c) watershed segmentation to (a) and d) watershed result superimposed to (a). Second row: e) smoothed image after the application of the ADF (40 iterations) and the ML (scale 3), f) color edge detection to (e), g) watershed segmentation to (e) and h) watershed result superimposed to (e).

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