Anais XII Simpósio Brasileiro de Sensoriamento Remoto, Goiânia, Brasil, 16-21 abril 2005, INPE, p. 4295-4302.

Enhanced filter using coefficients optimized for images Lansat

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Abstractc. In this study accomplish several experiments with the filters optimized of weights, through different bases of the transformed wavelet. Our goal was to determine a filter that it introduces a good highlight in the images of the orbital optical sensors. They were used one image of the city of Campinas of the interior of the state of São Paulo in Brazil. The results were best when compared to the obtained with the ideal filter of good used contrast in this study.

Keywords: multiscale analysis, filtering, Landsat, edge detection, contrast measure.

1. Introduction

1.1 Problem

Multiscales analysis was used in this study for different terms borders scales contained in a same image and that is considered as an only border in the linear filtration. The linear filtration introduces good results in terms of contrast however is not so good to hand different scales.

The enhanced or restored image *g* may be undesirable if noise in the original image *f* is amplified by *H*. By Weber`s Law and the masking effect suggest the following nonlinear approach to image enhancement

Let *L* denotes a linear filter that is tuned to a specific type of local image feature. By "local" we mean that the output image *Lf* at the point *(x,y)* depends only on the local neighborhood of about *(x,y)*. By "tuned" we mean that $|Lf(x,y)|$ is large if a local image feature, such as an edge or region of high intensity (high local mean), is near *(x,y)* in *f*. A weighted high pass filter is defined by the mapping

$$f(x,y)\ \alpha\ \ H_w f(x,y) = |Lf(x,y)|^p Hf(x,y), \quad p \geq 1.$$

Here, $|Lf|^p$ is the image formed by raising every point $Lf(x,y)$ in the image *Lf* to the p-th power. The image $|Lf|^p$ "weights" the high pass filters image *Hf* point wise according to the strength of the local features associated with *L*. For instance, if *L* corresponds to a local mean, then $H_w f$ is roughly proportional the image obtained by applying *H* only in regions with high local mean. If *L* is a local edge-detector, then $H_w f$ is proportional to the output image obtained by applying *H* only in regions where an edge is detected Roberts (1997).

The notion of multiscale signal analysis is motivated by the need to detect and characterize the edges of small and large objects alike. In an image, different structures give rise to edges at varying scales-small correspond to fine detail and large scales correspond to gross structure. In order to detect all image edges, one must study the image at each scale. Multi-scale image processing tools include scale space, wavelet transforms.

To analyze discrete images, we use an undecimated two channel filter bank with discrete analysis filters *h* and *g* and a range of scales *J* limited by the number of pixels in the image. In practice, the choice of *J* is problem-dependent, but prior information may suggest a reasonable choice depending on which types of features are dominant in the image under study Mallat (1992).

2. Optimal Weighted High Pass Filters

We can easily formulate the mean-weighted high pass filter in the multiscale framework by *Hf* in (1):

$$\left\{ \left|S_{2^j} f\right|^p Hf : j = 1,\ldots\ldots, j,\; p = 1,\ldots\ldots, P \right\} \tag{1}$$

The exponent *p* controls the relative weighting in light and dark regions; increasing *p* tends to emphasize areas of peak intensity. The scale bound *J* limits the range of scales used for local feature detection. *J* acts as a regularization parameter: a small value of *J* gives maximum regularization by focusing the filters on only very local feature, while a large value allows the filters to incorporate more global, gross structure at the expense of less regularization. In practice, the choice of *J* is problem-dependent, but priori information may suggest a reasonable choice depending on which types of features are dominant in the image under study.

3. Multiscale Edge-Weighted Filters

We define the detail modulus as

$$\left|D_{2^j} f(x,y)\right| = \sqrt{\left|W_{2^j}^h f(x,y)^2\right| + \left|W_{2^j}^v f(x,y)\right|^2 + \left|W_{2^j}^d f(x,y)\right|^2}$$

Point wise multiplication of the high pass image *Hf* with $\left|D_{2^j} f\right|^p$. The multiscale analysis produces a set of edge-weights high pass filters; each is tuned to edges at a prescribed scale:

$$\left\{ \left|D_{2^j} f\right|^p Hf : j = 1,\ldots.., J,\; p = 1,\ldots..., P \right\}. \tag{2}$$

Increasing the exponent *p* tends to localize the weighting to areas where the detail modulus has local maxima.

4. Optimal Filter Design

Multiscale analysis provides a suite of weighted high pass filters, (1) and (2), suitable for image enhancement. If we consider the collection of filtered versions of f

$$C_f = \left\{ \sum_{j=1}^{J} \sum_{p=1}^{P} \alpha_{j,p} \left|D_{2^j} f\right|^p Hf + \beta_{j,p} \left|S_{2^j} f\right|^p Hf \right\}$$

with arbitrary real coefficients $\{\alpha_{j,p}, \beta_{j,p}\}$. The collection C_f is quite general. The optimal weighted high pass filtered image $H_{opt} f$ is the projection of the linear high pass filtered image onto the subspace spanned by the set of weighted high pass filtered images. We can compute the optimal image by adjusting the filter parameters $\{\alpha_{j,p}, \beta_{j,p}\}$. Specifically, we have

$$H_{opt} f = \arg_{H_w f \in C_f} \min \| H_w f - Hf \|_F^2$$

where we have chosen the Frobeniuns norm for computational convenience.

The optimal filter H_{opt} is unique and can be computed in a simple fashion. First let

$$d_{j,p} = vec\left(\left| D_{2^j} f \right|^p Hf \right);$$
$$s_{j,p} = vec\left(\left| S_{2^j} f \right|^p Hf \right);$$
$$h = vec(Hf),$$

where "*vec*" is the operator that forms a column vector from a matrix by its columns. Now define the matrix $X = [d_{1,1},\dots, d_{j,p}, s_{1,1},\dots, s_{J,P}]$ and the parameter vector $\gamma = [\alpha_{1,1},\dots,\alpha_{j,p}\beta_{1,1},\dots,\beta_{j,p}]^T$. The optimal weighted high pass image, in vectorized form, is given by

$$h_{opt} = X\gamma_{opt}$$

where,

$$\gamma_{opt} = \arg_{\gamma \in R^{2jp}} \| X\gamma - h \|_2^2 = (X^T X)^{-1} X^T h.$$

We briefly describe an adaptive filter that optimally adjusts its weighting coefficients at each point in image. Using these parameters, the output of the locally optimal weighted high pass filter at the point (*x, y*) and $B(x, y)$ is a local neighborhood about (*x, y*), given by

$$H_{opt}(x, y) = X(x, y)\gamma_{opt}(x, y)$$

where,

$$\gamma_{opt}(x, y) = \arg_{\gamma \in R^{2jp}} \| X\gamma - h \|_{B(x,y)}$$

5. Applications

The experiments was used two images one of references Barbara and an image of the optical sensor Landsat, band TM3 of the city of Campinas of the State of São Paulo Brazil.

In Barbara's original image **Illustration 1(a)**, we apply the filter (h_L) to simulate the effect of the observed image, obtain the **Illustration 2(b)**. In the **Illustration 2(c)** we have filtration of the **Illustration 2(b)** by the lineal filter (h_H) and in the Holes 2(d), (e) show their filtrations by the filters MF and *DB4* respectively. We repeat the experiment now for the observed image **Illustration 3(a)** with the same filters: h_H obtain the image of the **Illustration 3(b)**, FM have the image of the **Illustration 3(c)** and finally DB4 who corresponds the **Illustration 3(d)**. Below used filters:

h_L = [1 0 1;0 4 0; 1 0 1] = Low *pass;*
h_H = [0 -1 0;-1 5 -1; 0 -1 0] = *High pass;*

High pass filter:
FM = [0.0078125 0.054685 0.171875 -0.171875 -0.054685 -0.0078125]; Mallat & Zhong (1992);
DB4 = [-0.24 0.71 -0.62 -0.03 0.18 0.03 -0.03 -0.01]; Daubechies;

Low pass filter:
FM = [0.0078125 0.046875 0.1171875 0.65625 0.1171875 0.046875 0.0078125]; Mallat & Zhong (1992);
DB4= [-0.03 0.03 0.04 -0.21 -0.01 0.62 0.71 0.22];
Daubechies;

5.1 Visual Analysis

The first evaluation of the methodology is the visual analysis of the percolated images. The resolution loss analysis by the application of a filtration is a qualitative approach most of the time. It visually is difficult to analyze an image with regard to the false borders creation and the contrast increase once that the quality of the analyzed images is very reasonable and most alterations are not sensitive to the human eye.

5.2 Borders Detection

The borders detection is one of the commoner operations used in the images analysis and there are lots of algorithms in the literature specialized to highlight and to detect borders.

A borders detector can fail, when relating a nonexistent border; this it can be due to the noise, or simply to a bad drawing or a filtration. In addition, a borders detector can fail to when not relate a pixel of an existing border. Other fault situation occurs when the position of the pixel of a border is weak. In this research was adopted the method defined by Canny (1986) for evaluation regarding borders detection.

The borders detector of Canny was chosen to for be one of the great existing detectors, for using near principles to the of a filtration, like a filtration, besides the results for images of optical sensors have been superior regarding tried traditional methods as Sobel, Prewitt, Roberts, among others

Like quantitative measure, in order to validate the performance of filtering techniques for images of orbital sensors, was adopted the merit illustration of Pratt (1978), in the equation below:

$$MDB = \frac{1}{\max\{I_A, I_i\}} \sum_{i=1}^{I_A} \frac{1}{1 + \delta\, e_i^2},$$

where I_A it corresponds to the number of detected dots, I_i to the number of dots of the ideal border, δ represents a constant of scale and e_i corresponds to the distance between detected dot and the ideal border.

The image of note that was used, to if measure MDB (border detection measure) is alike to 1.9504, because it introduces noise. If the used image was without noise the value of *MDB* is 1, which does not occur in this study, logo the value to be better should be nearest of 1 to a perfect border **Table 1**, being the value of the variable *MDB* reduced how much larger the mistake in the borders map. For the variable δ was adopted the value 1/9, suggested in Pratt (1978).

5.3 Contrast Measure

We want select images that have the highlighted borders and that improve the contrast. We propose a contrast measure in order to detect the contrast in the original image and post-filtration for analysis of the criterion of the contrast. Like contrast measure it adopted an expression defined by Morrow (1992). As,

$$MC = \frac{max(I) - min(I)}{max(I) + min(I)}$$

where I it corresponds to the image to what the contrast measure will be submitted. The measure will be obtained regarding the ash levels of the image I. It waits that after the filtration the value MC (contrast measure) whether you keep or it increase, but the borders of the image be highlighted. As well as the detection measure of introduced border, the contrast measure of the percolated image will be compared regarding a free image of noise (synthetical), which should introduce maximum contrast, and regarding the original image. The images were submitted to the following

5.3.1 Methodology:

1 -It calculates the contrast measure in the reference image;
2 - It calculates the contrast measure in the original image;
3 - It evaluates contrast alteration in the image percolated regarding the synthetical image.

In the results of measure of obtained contrast, the value in the reference image should be the maximum value regarding the too much. MC is satisfactory when the contrast in the percolated image is at least alike to the original, or when lower than the original introduces highlight of the borders.

Soon after the **table 2** describes the data measured with the observed image (IO) and the synthetical image.

IO=observed Image;
IFLP=Image percolated with Laplace's Filter;
IFLM=Image percolated with Laplace and base Mallat and Zhong;
IFLDB4=Image percolated with Laplace and base DB4.

Table 1. For observed image.

	IO	IFLP	IFLM	IFLDB4
MC	0.733	1	1	1
MDB	1.9504	1.1677	1.658	1.2559

IOs=synthetical original Image;
IFLPs=synthetical Image percolated with Laplace's Filter;
IFLMs=synthetical Image percolated with Laplace and base Mallat and Zhong;
IFLDB4s=synthetical Image percolated with Laplace and base DB4.

Table 2. For synthetical image.

	IOs	IFLPs	IFLMs	IFLDB4s
MC	0.8450	0.8959	0.9767	1
MDB	1.3103	1.1262	1.1027	1.2816

6. Conclusion

The numeric results of contrast and border indicate that the utilization of the base BD4, it was to what it introduced the best results when compared with the base filtration of Mallat & Zhong (1992). The results were doing well evaluated by the quantitative measures of contrast and border, indicating that the contrast is in the observed image is satisfactory for the three filtration in when that the borders measures show that the lineal filter creates falser borders regarding the filter DB4. Logo, the filtration with DB4 can be used with more precision in relation the other.

7. References

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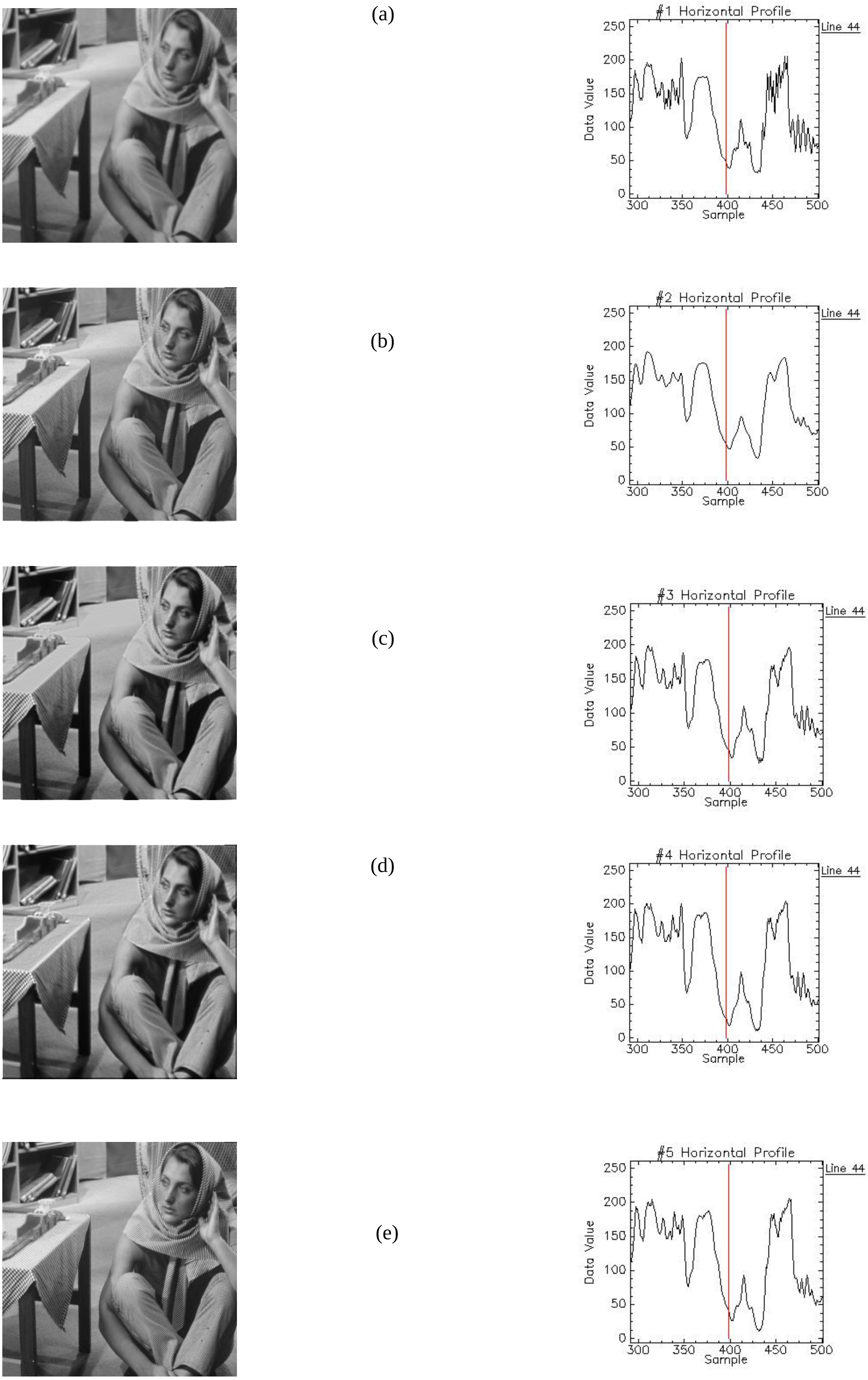
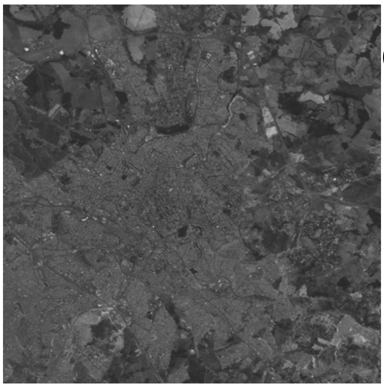
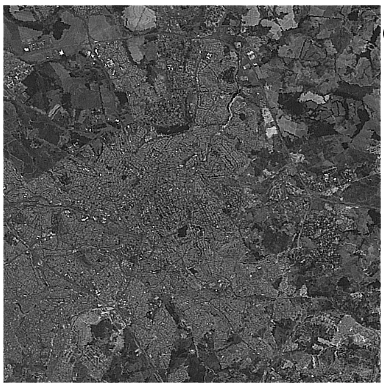


Figure 1. It shows the images prosecuted by filters indicated by (a), (b), (c), (d) and (e).


(a)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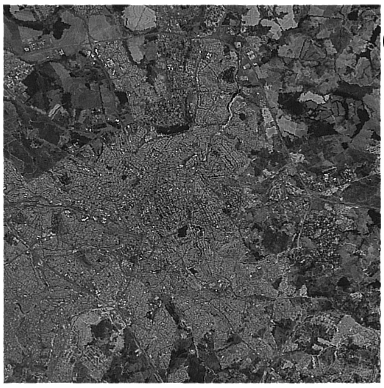

(c)

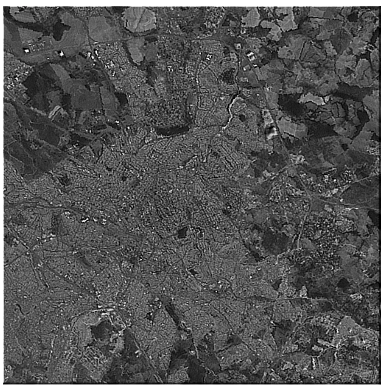
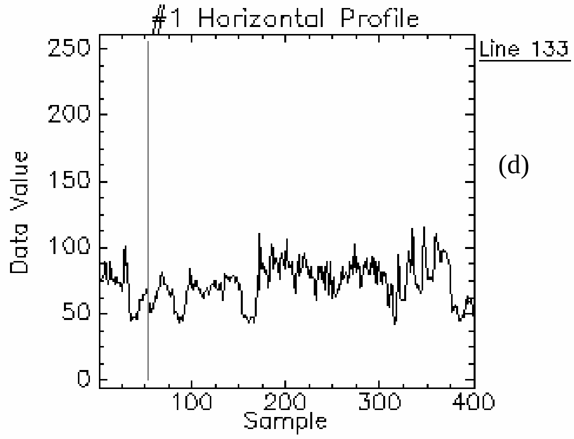
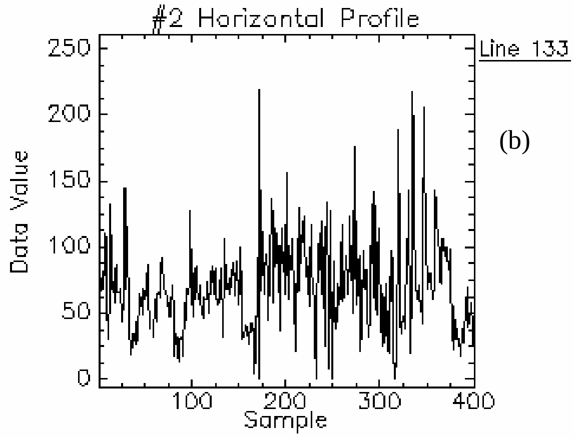

(d)

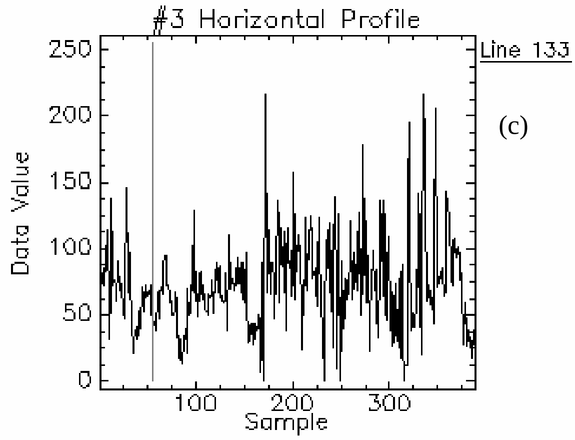
Figure 3. It shows the images prosecuted by filters in the Illustration 3(a), (b), (c) and (d).



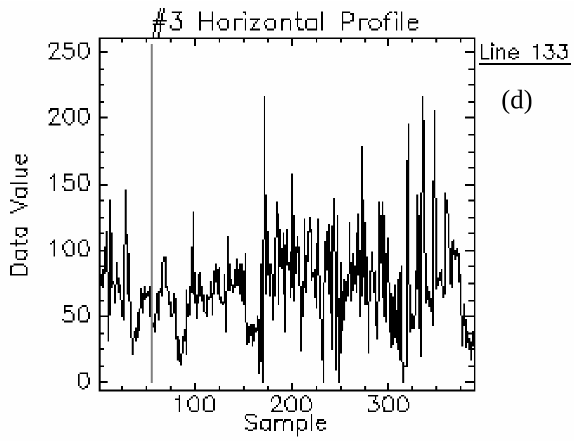
(d)



(b)



(c)



(d)

Figure 2. It shows the images prosecuted in the Illustration 2(a), (b), (c) and (d).