SEGMENTATION AND OBJECT EXTRACTION FROM ANISOTROPIC DIFFUSION FILTERED LIDAR INTENSITY DATA

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ABSTRACT:

LiDAR technology provides two different kinds of data: elevation, obtained by differences in time of the emitted and received laser signal; and intensity, obtained by differences of reflected laser beam according to different material present on the surface. Focusing on the increasing use of LiDAR technology, this paper reports a research of segmentation applied to LiDAR intensity data. The integration of both LiDAR elevation and intensity data permits their combination to mine information of scanned surface integrating object-based classification. Our research hypothesizes that LiDAR intensity images contain significant information about the objects sensed by the LiDAR sensor, and that segmentation can be conducted to detect semi-homogeneous objects of interest. However within the intensity data there also exists noise and signal eccentricity caused by sensor scanning patterns and receiver's adjusted gain response. Traditional low-pass filters have been used to minimize this problem, but caused blurred edges of objects of interest, which led to inefficient segmentation processing. Anisotropic diffusion filtering provides smoothing of intra-region areas preferentially over inter-region areas, thereby providing a good prospective tool for removing unwanted noise and preserving the edges of desired objects. This research compares different segmentation parameters over three images: an original LiDAR intensity image, a customized kernel low-pass filtered image and an anisotropic diffused filtered image. Kernel and anisotropic diffusion filtering parameters were adjusted to produce test images resulting in the effective removal of noise and artifacts as determined through visual inspection. Considering roads and buildings as objects of interest, comparisons between objects generated by segmentation and real objects were performed.

1. INTRODUCTION

A typical LiDAR (*Light Intensity Detection and Ranging*) system consists of a laser range finder, differential GPS, inertial navigation sensors, computer to process and store data and optionally other auxiliary devices onboard the aircraft. Commercially available products from LiDAR acquisitions may provide elevation data and intensity data, both of which may be utilized to provide characteristics of objects observed. LiDAR data are usually acquired as a set of overlapping strips, each consisting of multiple scan lines. Considering cost-effectiveness, efficiency, and accuracy of survey technology, applications employing LiDAR data as well as integration of LiDAR and high resolution multi-spectral imagery are increasing. The capability of making effective use of both LiDAR elevation and intensity data simultaneously for object extraction is real, however improvements in terms of processing and best use of these data present challenges, some of which are addressed in this application.

Regarding the effective use of LiDAR technology, object-based approaches presents high potential to join both elevation and intensity data on the classification scheme. However, the intensity data provides lower quality images compared to traditional panchromatic images. This limitation may be explained by the limited spectral range employed on the laser bundle as well as excessive noise and artifacts caused by the sensor scanning. According Song et all (2002), to remove noise from the images, mean filters or median filters are usually used, however they report significant increases on separability of features after using a krigging filter, considering statistic characteristics of objects of interest. Unfortunately, these approaches blurred the edges of objects when removing noises and artifacts. This effect is contrary to the goal of preserving the borders of urban man-made features in scenes (buildings and roads) to enable accurate determination of their geometric parameters. Since object-based classification can be supported by information content that extends the pixel information, geometry and topology characteristics are considered as significant inputs.

The present work has been motivated by the increasing use of LiDAR technology and by the need to improve classification results by integrating LiDAR products with other techniques of digital image processing and information extraction.

The present paper is structured by introductory concepts for LiDAR, anisotropic diffusion and object-based classification. In methodology, the data and study area, as well the image processing and analysis methods are reported. Results, discussion and conclusions are presented in sequence.

2. CONCEPTS

Gutierrez et al (2001) define that in Airborne Laser Surface Mapping (ALSM) elevation points are captured using three sets of data: laser ranges, platform position and orientation and calibration data. GPS receiver's record pseudo-range and phase information for post-processing. Information of orientation comes from an Inertial Measurement Unit (IMU) that contains three orthogonal accelerometers and gyroscopes, illustrates on Figure 1. Calibration requires very precise measurements on the ground that support detection of scanner roll and pitch bias corrections, scanner scale correction as well as timing adjustments.

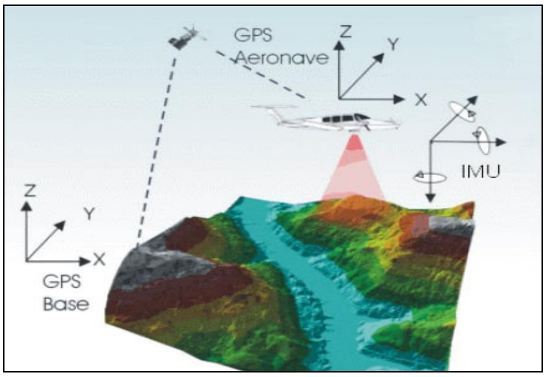

Figure 1. Components of LiDAR system. Kersting et al 2005.

2.1 LiDAR Intensity Image

Coren et al (2005) relate that the intensity of reflectance to the laser beam may be used to generate intensity images allowing representation of territory features. Intensity is defined as a ratio of strength of reflected and emitted light, as directly influenced by the reflectance of the objects as well as by the bundle incident angle.
The amplitude of the signal of the laser scan return, measured by the system, effectively does not allow properly reconstructing ground reflectance, however LiDAR intensity data contains significant information about the objects sensed by the LiDAR sensor.
Nevertheless, within the intensity data there are noise and signal eccentricities caused by sensor scanning patterns, the nature of the objects being scanned, and the receiver's adjusted gain response, as shown in Figure 2.

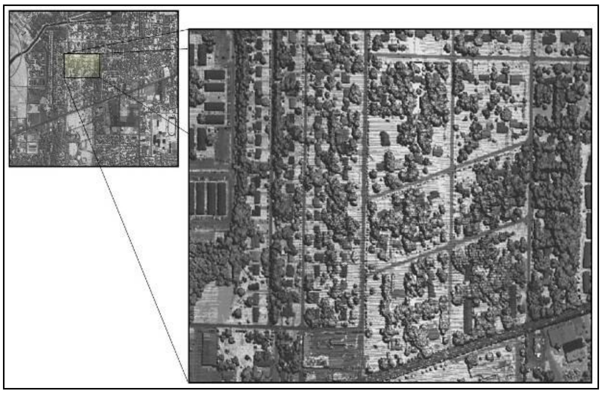

Figure 2. LiDAR intensity image and detailed windows showing noises over grass, trees, buildings and streets.

To effectively mine the information content of LiDAR intensity data for use in enhanced classification efforts, various filtering approaches may be employed including low-pass/median filter and krigging interpolation. However, considering the need to preserve the geometric characteristics of desired urban features, efforts are required to minimize adverse blurring of object edges caused by filter-processing of the LiDAR intensity image.

2.2 Anisotropic Diffusion Filter

In digital image processing, scale-space consists of a family of image descriptions varying from fine to coarse representation of the details, as defined by Acton et al (1992). Perona and Malik (1990) used a heat diffusion equation to compute the scale-space iteratively.

$$S_{i,j,T} = \lambda\left(C_{i,j,T} \nabla S\right) \tag{1}$$

where ∇ = gradient operator
λ = divergence operator
$C_{i,j,}$ = parameter for heat diffusion for pixel (i,j)
T = iteration

Keeping $C_{i,j,T}$ as constant the diffusion will result in a isotropic Gaussian smoothing. However, varying the diffusion coefficients according to the magnitude of the local image gradient, an anisotropic smoothing is obtained.

$$S_{i,j,(T+1)} = S_{i,j,T} + \lambda\left(C_{(i,j)_D} \nabla_D\right) \tag{2}$$

where $C_{i,j,}$ = parameter for heat diffusion for pixel (i,j)
∇ = gradient operator
D = direction (North, South, East, West)
T = iteration

The diffusion coefficients discourage inter-region bleeding by inhibiting neighborhood smoothing where the local image gradient is large and a region boundary is present (Acton et al, 1992). The parameter λ is included to control the magnitude of the smoothing. However, Black et al (1998) suggested an approach for anisotropic diffusion based on robust statistical analysis to improve the quality of the edges. Assuming a Gaussian-noisy image with mean equal zero and small standard deviation, a Robust Anisotropic Diffusion approach was proposed based on the criteria:

$$\min_S \sum_{i,j \in S} \sum_{p \in \eta_{i,j}} \rho\left(S_p - S_{i,j}, \sigma\right) \tag{3}$$

where $S_{i,j}$ = image value for the pixel (i,j)
$\eta_{i,j}$ = spatial neighborhood for the pixel (i,j)
ρ = robust error
σ = scale parameter

$$S_{i,j,(T+1)} = S_{i,j,T} + \frac{\lambda}{\left|\eta_{i,j}\right|} \sum_{\rho \in \eta_{i,j}} \psi\left(S_p - S_{i,j}, \sigma\right) \tag{4}$$

where $\psi = \rho'$ (influence function)
T = iteration

The influence function provides ways to choose and evaluate the robust error. To preserve edges over homogeneous regions, the larger gradient values must be rejected by the influence function. The goal is to improve the computation for mean of intra-region neighbor's pixels and reduce the computation for mean inter-region (Giacomontone 2005). Tukey's biweight was choose by Black et al (1998) as criteria for edge spot due to faster convergence and finer detailed edges produced when compared to previous approaches.

2.3 Segmentation and Object-Based Classification

Considering that image information present in a remote sensing scene are fractal in nature Blaschke and Strobl (2001), the more characteristics (geometric, spectral and topologic) for these objects, the more realistic the classification can be. Object attributes provide a wide range of information to discriminate different land cover/use over in comparison to pixel attributes. Many recent publications have reported increasing the accuracy of classification using object-based versus traditional pixel-based approaches. Comparisons between traditional pixel-based and object-based methodologies have demonstrated how powerful the new technology is, especially for high resolution imagery. To detect these real objects, segmentation is normally applied.

Segmentation can be understood as the subdivision of original image into small and homogeneous regions until the objects of interest are isolated. According to Gonzales and Woods (1993), the automation of segmentation is one of the hardest tasks for digital image processing.

Object-based classification considers more information to compose class decision rules than pixel values. Segments, composed by pixels, provide spectral and geometric information, moreover the decision rules can be enhanced with contextual informational. In other words, more than simple pixel's color can be used to discriminate different objects. Parameters extracted from shape (area, rectangular fitting, length, etc.) and neighbor's relationship can be included on classification strategies to promote better discrimination of objects with similar spectral responses.

Also, in object-based classification, more than one layer of information has been employed with success to supply information for the classification rules. Considering segmentation as the first step for the classification approach, complementary information of desired urban objects can be mined from the other layers as digital terrain/elevation model or multi-spectral images.

Due to the perfect fitting of LiDAR intensity image and LiDAR elevation data, the segmentation process can be computed on intensity image and complementary elevation derived maps can be used to support the process.

3. METHODOLOGY

3.1 Study Area and Data

The study area located on the Mississippi coast was selected by researchers for acquiring LiDAR data, conducted in 2003 by Laser Mapping Specialists, Inc. for areas in and around Gulfport, MS. The area is coastal in setting with a temperate to hot climate, seasonally variable rainfall, and significant vegetation coverage year-round. Many live oak trees predominate in urban areas and obscure the aerial view of roads, boulevards, and buildings making analysis of LiDAR and aerial photography difficult.

The relative low-lying, gently sloped to flat terrain of the Mississippi Gulf coast with it dense vegetation and year-round leaf-on conditions for large live oaks presents a challenging environment that is particularly well-suited for developing enhanced methods for classification and feature extraction that would lead to enhanced elevation surface processing as well as improved land use classification.

Considering processing, three software solution where employed in completing this research effort:

- Erdas Imagine, to subset areas of interest, compute low-pass filtering as well as calculate the difference between both resultant images ;
- IMG library, to compute the anisotropic diffusion ; and
- Definiens eCognition, for segmentation and classification.

3.2 Filtering

Two different approaches were employed to filter the original LiDAR intensity image: a customized kernel low-pass filter and an anisotropic diffusion filter.

Regarding the traditional low-pass filtering, some tests were previously performed using mean and median filter on behalf of effective removal of noise and artifacts present on original image as determined through visual inspection. A Kernel low-pass 5x5 pixels' window (Figure 3) was due to best results reached. Due to horizontal characteristic of the artifacts, as showed on Figure 2 and Figure 4 on top, the filter was customized to perform as horizontal filter.

1	*1*	*1*	*1*	*1*
1	*2*	*2*	*2*	*1*
1	*1*	*12*	*1*	*1*
1	*2*	*2*	*2*	*1*
1	*1*	*1*	*1*	*1*

Figure 3. Kernel's 5x5 filter employed to remove artifacts of LiDAR intensity image.

The next step was generating a new filtered image through anisotropic diffusion. However anisotropic diffusion by using scale-space approach is not so recent, it is not available on remote sensing packages. Then, the IMG library -a free C++ digital image processing library- was employed here.

Different combinations of parameters were tested to obtain the least noisy image possible. To compute the anisotropic diffusion, the parameters required by IMG library are:

- number of iterations
- sigma (Gaussian standard deviation)
- method (Perona-Malik or Tukey)
- size of structure element
- lambda (smoothing parameter)

Again, the best result was selected based on visual inspection of effective noise/artifacts removal and edges preservation. The smaller the sigma value, the finer the resultant image. Also, many iterations sometimes did not improve the quality, but resulted in excessive computational expense. An important parameter considered was the structure element, or window-size. A larger window destroys original information present in an image, including edges.

Due to the particular characteristics of the parameters of anisotropic diffusion filter, as well as the particular characteristics of LiDAR intensity image used, the best results was obtained with 25 iterations, sigma 0.01, Tukey's method, lambda 1 and a 3x3 pixel's size structure element.

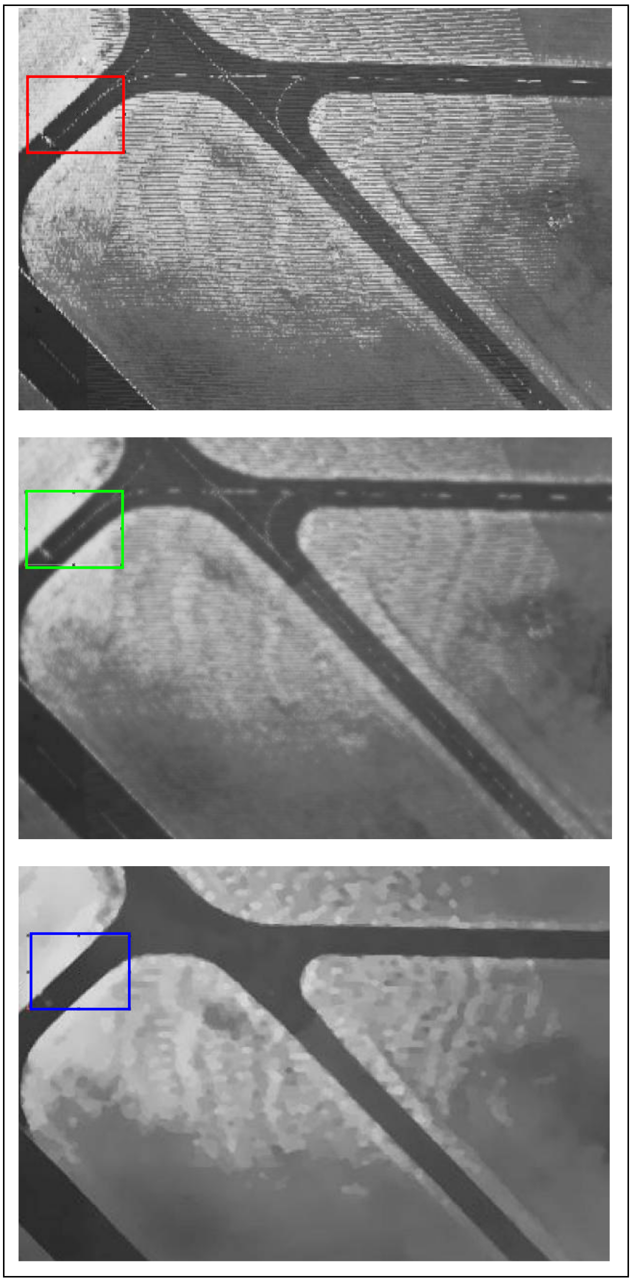

Figure 4. Airport lane selected as sample area for original LiDAR intensity image on top, kernel low-pass filtered image on middle and anisotropic diffused image on bottom.

The selected area above is part of an airport and differences in elevation for runway lanes and grassy areas are typically smaller than their difference of intensity. In cases such as this, the use of intensity data will likely provide better class separation between objects than elevation data.

A sensible reduction of noise can be found for filtered images on Figure 4, however, the surface profiles of intensity shown on Figure 5 visually illustrates relative performance of the various methods employed for noise reduction.

Comparing the low-pass filtered image (middle) and the original image (top), within the noise reduction, we observe blurred edges for the airport runway lanes. In the surface profile, a smoothed scarp (reduction of abrupt slope) is found. However, regarding the result of anisotropic diffusion filter, borders are preserved and noises are effectively reduced (Figures 4 and 5 – bottom).

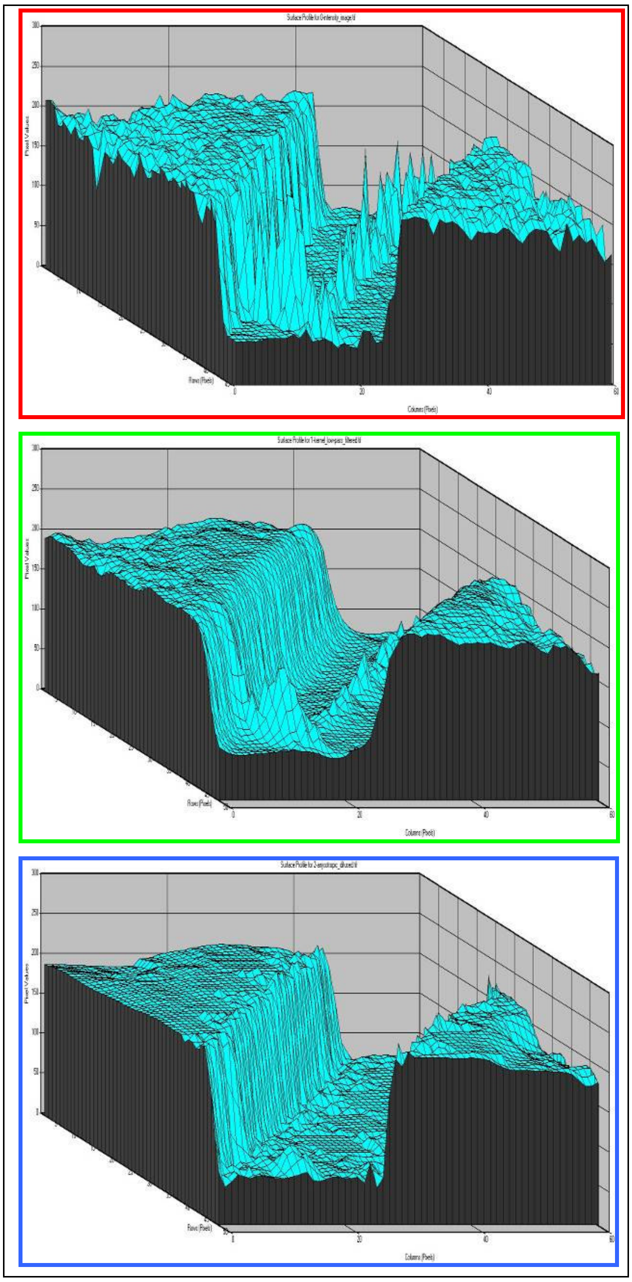

Figure 5. Surface profiles for each sample area of Figure 3 Airport lane selected as sample area for original LiDAR intensity image on top, for kernel low-pass filtered image on middle and for anisotropic diffused image on bottom.

However, with a reduction of noise, some original information will unavoidably be lost regardless of processing method. Typical examples are the painted stripes on lanes. These objects were not detected by anisotropic diffusion filter due to size of the structure element. They are considered artifacts and their elimination is not deemed problematic to the process.

3.3 Segmentation

Considering the 1-meter resolution of LiDAR data over an urban area, the segmentation was developed using different parameters, regarding roads and buildings as objects of interested. The same setting was used for each image. Three sets of parameters -from finer to coarser- were tested,

totalizing nine segmentations. Using small-scale factor on the original intensity image, a large amount of useless segments was created due to artifacts detection. For both kernel filtered and anisotropic diffused images, significant reduction of number of segments occurred.
However, due to the blurred aspect of kernel images, edges of objects of interest were affected. With the segmentation, some undesired objects were created on the borders because the smoothing transition between objects. Analyzing the anisotropic diffused image, significant reduction of erroneous segments was found for the edges of objects of interest.
Creating segments that fit with urban objects using original intensity image was practically impossible due to their excessive noise. On the low-pass filtered image, the created segments look more realistic, fitting with roads, however small segments were computed for the border by the smooth transition. Results on anisotropic diffusion showed better fitting and of segments and desired urban objects.

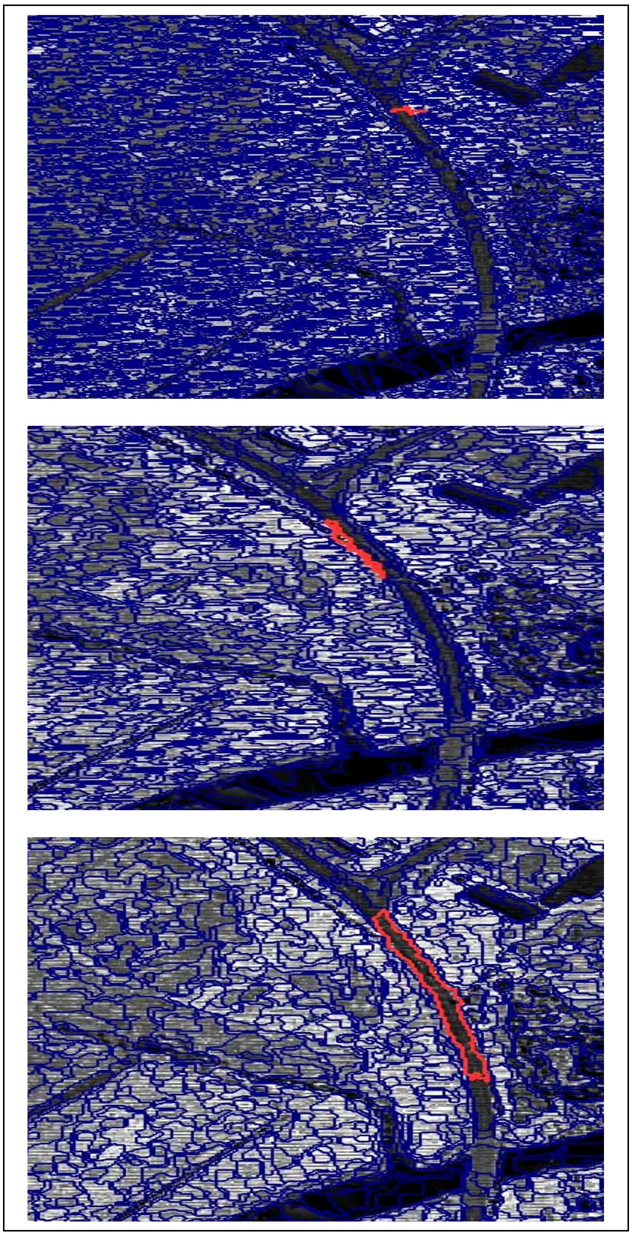

Figure 6. Overlay of different segmentations and LiDAR intensity image. Results of original intensity on top, low-pass filtered on middle and for anisotropic diffused on bottom.

Otherwise, visual analyses on segmented images using large-scale factor show few difference between the three methods. Details on the edges of objects of interest are automatically lost when coarse segments are created.

IMAGE	SCALE	SHAPE	COMP	# OBJECTS
original	10	0.1	0.5	190.435
original	10	0.1	0.1	187.779
original	25	0.1	0.1	28.665
low-pass	10	0.1	0.5	92.858
low-pass	10	0.1	0.1	90.061
low-pass	25	0.1	0.1	19.415
anis. diffusion	10	0.1	0.5	76.161
anis. diffusion	10	0.1	0.1	74.422
anis. diffusion	25	0.1	0.1	18.931

Table 1. Parameter used to compute the segmentation and number of objects generated.

4. RESULTS AND DISCUSSION

In this paper different segmentation approaches are presented and the results are compared for segmenting an anisotropic diffusion filtered image to the original image as well as to the low-pass kernel filtered image, with the objective of defining enhanced methods that apply to data fusion and object-based classification
In this research, three images were used: an original LiDAR intensity image, a customized kernel low-pass filtered image and an anisotropic diffused filtered image. The parameters for kernel low-pass filter and anisotropic diffusion process were adjusted to produce test images resulting in the effective removal of noise and artifacts as determined through visual inspection. The best result for anisotropic diffusion filtering used 25 iterations, sigma 0.01, lambda 1 and window size 3 through Tukey's method. For kernel filtering, a customized 5x5 horizontal filter was chosen.
Analyzing both filtered images, we could see effective removal of artifacts and noise, but also excessive blurring for the edges when low-pass filtering was applied. The Figure 7 shows the difference of low-pass filtered and anisotropic diffused image. Dark areas indicate internal features that are minimized by the anisotropic diffusion method, and bright areas indicate edges and noises that are maintained on low-pass filtered image.

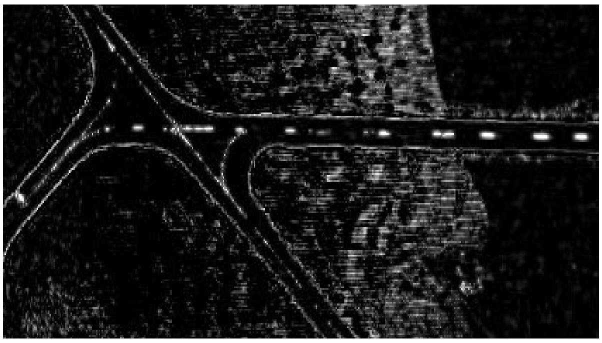

Figure 7. Difference of low-pass filtered image and anisotropic diffused filtered image.

Some image details were lost during the anisotropic diffusion filtering largely due to the size of the structure element. Painted stripes on lanes illustrated on Figure 7 were

completely removed with the new approach in comparison with low-pass filtering.
Regarding the potential of LiDAR intensity images as a base layer for segmentation as well as the complete interaction with elevation data; and regarding the artifacts present in these data, the results of this research indicate that anisotropic diffusion filtering provides a good pre-processing technique. Time to complete processing per filtering method was not computed in this paper.

5. CONCLUSIONS AND FUTURE WORKS

Anisotropic diffusion filtering provides a characteristic smoothing of intra-region areas preferentially over inter-region areas, thereby providing a good prospective tool for removing unwanted noise and preserving the edges of desired objects. Considering the increasing use of LiDAR applications, as well as the increasing use of object-based classification, we believe the first results pointed out on this study can be considered a good indicator of the potential classification improvements that might be realized through using both technologies together. The resultant image may be used as a segmentation layer to mine the feature space of the layers such as DTM, DSM, DTM slope, DSM slope plus multi-spectral image data to produce improved classification products. Nevertheless, more analyses must be considered, including small-scale segmentation to effectively define urban objects.

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IMG can be reached on http://www.lps.usp.br/~hae/software or contacting hae@lps.usp.br.