Filters Evaluation for Detection of Contours in Satellite Images for Cadaster Purposes

Luis Cadena, Alexey Kruglyakov, Franklin Cadena, Alexey Romanenko, Alexander Zotin.

Abstract— **The contour detection has an important role in image processing, especially in the detection and the extraction physical features, those which are useful to their enforcement in the analysis of cadasters. A new methodology is shown for processing satellite images using spatial filters. The contour of satellite images are obtained and compared with conventional processing filters. The results were obtained with the filters Sobel, Prewitt, Roberts, Canny, and LoG for processing satellite images and they were evaluated using Structural Similarity Index (SSIM) for measuring image quality.**

Index Terms— **satellite image, digital image, contour, filters Sobel, Prewitt Roberts, Canny, LoG. ssim.**

I. INTRODUCTION

The digital processing of images consists of algorithmic processes that transform an image into another in which certain information of interest is highlighted, and/or the information that is irrelevant to the application is attenuated or eliminated. Thus, image processing tasks include noise suppression, contrast enhancements, removal of undesirable effects on capture such as blurring or distortion by optical or motion effects, geometric mapping, color transformations, and so on.

The satellite images allow to obtain relevant information of the surface of the Earth to be able to quantify and to qualify the existing natural resources, the urban expansion, deforestation, deglaciation, etc.

Agricultural production, territorial organization, global warming, etc., validate the importance of the use of satellite images as a global means of capturing information for the inventory of natural resources. In this sense, one of the most relevant applications is the obtaining of cartography for cadastral purposes very important in the planning and administration of a territory; as well as the use and coverage of the existing soil in a geographic space. For this, different classification methods have been used, and restitution techniques have been used. Methods that mainly serve for low and medium resolution images; while today, new high-resolution satellites have been launched and even unmanned aerial vehicles are being used, which involve discrimination of smaller objects and the search for new classification methods to organize objects, as well as their Automation so that the user can generate studies of systems of agricultural production, afforestation, organization of the territory, environmental management, extraction of resources, etc.

Manuscript received July 02, 2017; This work was supported by Universidad de las Fuerzas Armadas ESPE, Av. Gral Ruminahui s/n, Sangolqui Ecuador.

L. Cadena, is with Electric and Electronic Department at Universidad de las Fuerzas Armadas ESPE, Av. Gral Ruminahui s/n, Sangolqui Ecuador. (phone: +593997221212; e-mails: ecuadorx@gmail.com).

F. Cadena is with College Juan Suarez Chacon, Quito, Ecuador (e-mail: fcfc041@gmail.com)

A. Kruglyakov is with Siberian Federal University, 79 Svobodny pr., 660041 Krasnoyarsk, Russia Federation (e-mail: piggsyy@gmail.com)

A. Romanenko is with Novosirbirsk State University, 630090, Novosibirsk-90, 2 Pirogova Str. Russia Federation (e-mail: romanenko.alexey@gmail.com)

A. Zotin is with Department of Informatics and Computer Techniques, Reshetnev Siberian State University of Science and Technology, 31 krasnoyarsky rabochy pr., Krasnoyarsk 660014, Russia Federation (e-mail: zotinkrs@gmail.com)

II. FILTERS FOR CONTOUR DETECTION AND SSIM MEASURE

Sobel operator computes the approximation of gradients along the horizontal (x) and the vertical (y) directions (2D spatial) of the image intensity function, at each pixel, and highlights regions corresponding to edges. Sobel edge detection is implemented using two 3x3 convolution masks or kernels, one for horizontal direction, and the other for vertical direction in an image, that approximate the derivative along the two directions [1-9]. Sobel operator uses the following filters:

$$H_x^S = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

and

$$H_y^S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

The two filters are almost identical with the filters used by Prewitt operator, excepting the weighting of the middle row (for horizontal kernel) and column (for vertical kernel): Sobel uses a weighting of 2 and -2, while Prewitt uses a weighting of 1 and-1. The local gradient components are computed as follows:

$$\nabla I(u,v) \approx \frac{1}{8}\begin{bmatrix} (I * H_x^S)(u,v) \\ (I * H_y^S)(u,v) \end{bmatrix}$$

Prewitt operator is a discrete operator which estimates the gradient of the image intensity function. It computes the approximations of the derivatives using two 3×3 kernels (masks), in order to find the localized orientation of each pixel in an image. Prewitt differs from Sobel operator only in the filters they use [1-9]. Prewitt operator used the following filters:

$$H_x^P = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

and

$$H_y^P = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}.$$

The local gradient components are obtained from the filter by scaling:

$$\nabla I(u,v) \approx \frac{1}{6}\begin{bmatrix} (I * H_x^P)(u,v) \\ (I * H_y^P)(u,v) \end{bmatrix}$$

The Roberts cross operator provides a simple approximation to the gradient magnitude:

$$G[f[i,j]] = |f[i,j] - f[i+1,j+1]| + |f[i+1,j] - f[i,j+1]|$$

Using convolution masks, this becomes:

$$G[f[i,j]] = |G_x| + |G_y|$$

Where G_x and G_y are calculated using the following masks:

$$G_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

$$G_y = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

The differences are computed at the interpolated point $\left[i+\frac{1}{2}, j+\frac{1}{2}\right]$. The Roberts operator is an approximation to the continuous gradient at that point and not at the point $[i,j]$ as might be expected.

The Canny edge detector is the first derivative of a Gaussian and closely approximates the operator that optimizes the product of signal-to-noise ratio and localization. The Canny edge detection algorithm is summarized by the following notation. Let $J[i,j]$ denote the image. The result from convolving the image with a Gaussian smoothing filter using separable filtering is an array of smoothed data,

$$S[i,j] = G[i,j;\sigma] * I[i,j]$$

where σ is the spread of the Gaussian and controls the degree of smoothing.

The gradient of the smoothed array $S[i,j]$ can be computed using the 2×2 first-difference approximations to produce two arrays $P[i,j]$ and $Q[i,j]$ for the x and y partial derivatives:

$$P[i,j] \approx (S[i,j+1] - S[i,j] + S[i+1,j+1] - S[i+1,j])/2$$
$$Q[i,j] \approx (S[i,j] - S[i+1,j] + S[i,j+1] - S[i+1,j+1])/2$$

The finite differences are averaged over the 2×2 square so that the x and y partial derivatives are computed at the same point in the image. The magnitude and orientation of the gradient can be computed from the standard formulas for rectangular-to-polar conversion:

$$M[i,j] = \sqrt{P[i,j]^2 + Q[i,j]^2}$$
$$\theta[i,j] = \arctan(Q[i,j], P[i,j])$$

where the arctan function takes two arguments and generates an angle over the entire circle of possible directions. These functions must be computed efficiently, preferably without using floating-point arithmetic. It is possible to compute the gradient magnitude and orientation from the partial derivatives by table lookup. The arctangent can be computed using mostly fixed-point arithmetic with a few essential floating-point calculations performed in software using integer and fixed-point arithmetic.

Canny Edge Detection algorithm:

1. Smooth the image with a Gaussian filter.
2. Compute the gradient magnitude and orientation using finite-difference approximations for the partial derivatives.
3. Apply nonmaxima suppression to the gradient magnitude.
4. Use the double thresholding algorithm to detect and link edges.

Laplacian of Gaussian (LoG), edge points detected by finding the zero crossings of the second derivative of the image intensity are very sensitive to noise. Therefore, it is desirable to filter out the noise before edge enhancement. To do this, the Laplacian of Gaussian (LoG), due to Marr and Hildreth, combines Gaussian filtering with the Laplacian for edge detection.

The fundamental characteristics of the Laplacian of Gaussian edge detector are:

1. The smoothing filter is a Gaussian.
2. The enhancement step is the second derivative (Laplacian in two dimensions).
3. The detection criterion is the presence of a zero crossing in the second derivative with a corresponding large peak in the first derivative.
4. The edge location can be estimated with subpixel resolution using linear interpolation.

In this approach, an image should first be convolved with a Gaussian filter. This step smooths an image and reduces noise. Isolated noise points and small structures will be filtered out. Since the smoothing will result in spreading of edges, the edge detector considers as edges only those pixels that have locally maximum gradient. This is achieved by using zero crossings of the second derivative. The Laplacian is used as the approximation of the second derivative in 2-D because it is an isotropic operator. To avoid detection of insignificant edges, only the zero crossings whose corresponding first derivative is above some threshold are selected as edge points.

The output of the LoG operator $h(x,y)$ is obtained by the convolution operation

$$h(x,y) = \nabla^2[(g(x,y) * f(x,y))]$$

Using the derivative rule for convolution,

$$h(x,y) = [\nabla^2 g(x,y)] * f(x,y)$$

where

$$\nabla^2 g(x,y) = \left(\frac{x^2 + y^2 - 2\sigma^2}{\sigma^4}\right) e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

is commonly called the Mexican hat operator. Thus, the following two methods are mathematically equivalent:

1.- Convolve the image with a Gaussian smoothing filter and compute the Laplacian of the result;

2.- Convolve the image with the linear filter that is the Laplacian of the Gaussian filter.

Smoothing is performed with a Gaussian filter, enhancement is done by transforming edges into zero crossings, and detection is done by detecting the zero crossings. It can be shown that the slope of the zero crossing depends on the contrast of the change in image intensity across the edge. The problem of combining edges obtained by applying different-size operators to images remains. In the above approach, edges at a particular resolution are obtained. To obtain real edges in an image, it may be necessary to combine information from operators at several filter sizes [1-9].

The structural similarity (SSIM) index is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. SSIM is used for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measurement or prediction of image quality is based on an initial uncompressed or distortion free image as reference. SSIM is designed to improve on traditional methods such as peak signal to noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human visual perception.

The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate absolute errors; on the other hand, SSIM is a perception based model that considers image degradation as perceived change in structural information, while also incorporating important perceptual phenomena, including both luminance masking and contrast masking terms. Structural information is the idea that the pixels have strong interdependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. Luminance masking is a phenomenon whereby image distortions (in this context) tend to be less visible in bright regions, while contrast masking is a phenomenon whereby distortions become less visible where there is significant activity or "texture" in the image. [10,11, 13-17]

The mean structural similarity index is computed as follows:

Firstly, the original and distorted images are divided into blocks of size 8 x 8 and then the blocks are converted into vectors. Secondly, two means and two standard derivations and one covariance value are computed from the images as:

$$\mu_x = \frac{1}{T}\sum_{i=1}^{T} x_i \qquad \mu_y = \frac{1}{T}\sum_{i=1}^{T} y_i$$

$$\sigma_x^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - \bar{x})^2$$

$$\sigma_y^2 = \frac{1}{T-1}\sum_{i=1}^{T}(y_i - \bar{y})^2$$

$$\sigma_{xy}^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - \bar{x})\,(y_i - \bar{y})$$

Thirdly, luminance, contrast, and structure comparisons based on statistical values are computed, the structural similarity index measure between images x and y is given by:

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}$$

where c_1 and c_2 are constants [11]

III. EXPERIMENTAL RESULTS

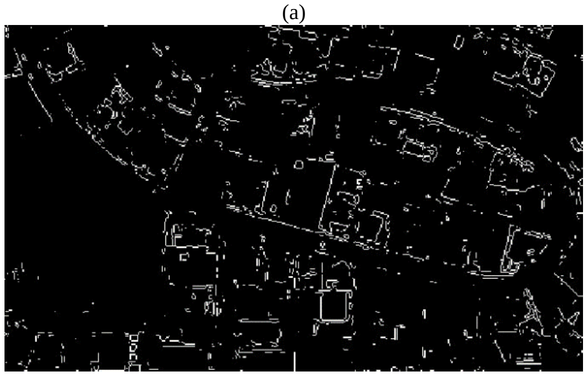
METHODOLOGY

First selected images were converted into gray images using the function in Matlab, then the metrics were implemented upon these images and last a comparison has been done between five objective evaluations, Structural Similarity Index (SSIM) metrics, by simulating it using Matlab software.

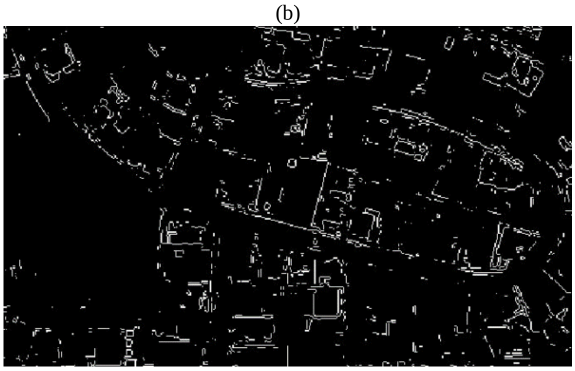
For the experiment used Notebook ASUS K75VJ core i7, 16Gb RAM, software Matlab 2015 (The MathWorks). [12]

The figure 2 show the results obtained from the contour search for the satellite image.

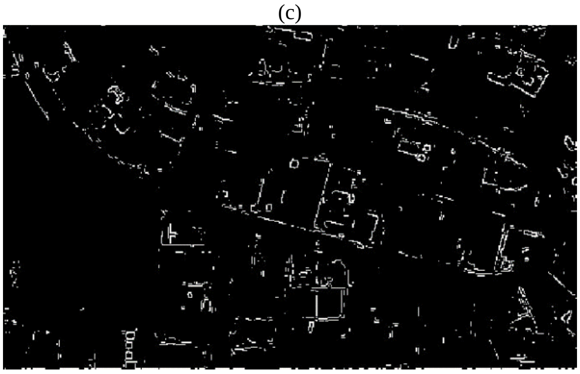
(a)



(b)



(c)



(d)

(e)

ISBN: 978-988-14047-5-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

(f)

Figure 2. Results of the find contour: original (a): Sobel (b); Prewitt (c); Roberts (d); Canny (e); LoG (f).

Figure 3. SSIM index Map. Mean ssim value is 0.9935 filter Canny vs Roberts

From Figure 2 and human visual interpretation, the best filter is Canny, then it is compared and evaluated the other filters with respect to the Canny filter with the SSIM metric and the results are shown in Table I.

TABLE I.
SSIM MEASURE IMAGE QUALITY FOR CONTOUR IMAGES

	Sobel	Prewitt	Roberts	Canny	LoG
Sobel	1.0000	0.9999	0.9990	0.9938	0.9966
Prewitt	0.9999	1.0000	0.9990	0.9938	0.9966
Roberts	0.9990	0.9990	1.0000	0.9935	0.9962
Canny	0.9938	0.9938	0.9935	1.0000	0.9954
LoG	0.9966	0.9966	0.9962	0.9954	1.0000

IV. CONCLUSIONS

The automated process decreases time, expense and provides users with another mechanism for obtaining contours of satellite images, effectively and reliably, will be used in cartography for cadastral purposes which is important for the planning and administration of a territory.

With the use of digital filters which in the last decades have taken great impetus for the treatment of images in different fields of science and in the case of the processing of satellite images better results are obtained in order to make better interpretations, it was determined that the Canny filter gives better visual result, but at the same time it is the filter that takes more time to run.

All used image quality metrics are objective measurements that are automatics and mathematical defined algorithms.

After applying filters for contour detection, it was select Canny filter as the best quality image. Measuring image quality for the five contour images gave the results included in Table I.

REFERENCES

[1] Antón-Rodríguez, M.; Díaz-Pernas, F. J.; Díez-Higuera, J. F.; Martínez-Zarzuela, M.; González-Ortega, D. & Boto-Giralda, D. Recognition of coloured and textured images through a multi-scale neural architecture with orientational filtering and chromatic diffusion. Neurocomputing, Vol. 72 (3713–3725). ISSN: 0925-2312. 2009.

[2] Canny J.A. Computational Approach to Edge Detection, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 8, No. 6, Nov. 1986.

[3] Davies E. Machine Vision: Theory, Algorithms and Practicalities, Academic Press.

[4] Daugman, J.G. (1980) Two-dimensional spectral analysis of cortical receptive field profiles. Vision Research, Vol. 20 (pp. 847-856). ISSN: 0042-6989. 2012.

[5] Gonzalez R.C., Woods R.E. Digital Image Processing. Second Edition. Prentice Hall.

[6] Grigorescu, C.; Petkov, N. & Westenberg, M.A. (2004). Contour and boundary detection improved by surround suppression of texture edges, Image and Vision Computing, Vol. 22, No. 8 (pp. 609-622). ISSN: 0262-8856. 2002.

[7] Kokkinos, I.; Deriche, R.; Faugeras, O. & Maragos, P. Computational analysis and learning for a biologically motivated model of boundary detection. Neurocomputing, Vol. 71, No. 10-12 (Jun. 2008) (pp. 1798-1812). ISSN: 0925-2312. 2008.

[8] Ramesh, J., Rangachar, K., Brian G,. S. Machine Vision. McGraw-Hill, Inc., ISBN 0-07-032018-7. 1995.

[9] Szeliski R. Computer vision. Algorithms and applications. Springer-Verlag London Limited. 2011.

[10] Wang Zhou, Alan C. Bovik, Hamid R. Sheikh, and Eero P. Simoncelli, "Image Quality Assessment: From Error Measurement to Structural Similarity", IEEE Transactions on Image Processing, Vol. 13, No.4, pp600-613, April 2004.

[11] Guan-Hao Chen, et al. Edge-based structural similarity for image quality assessment. 142440469X/06/$20.00 ©2006 IEEE. ICASSP 2006.

[12] The MathWorks. Inc. Image Processing Toolbox™ User's Guide. 2015.

[13] Wen Xu and G.Hauske, "Picture Quality Evaluation Based on Error Segmentation",SPIE vol.2308,pp.1454-1465,1994

[14] M.Miyahara,K.Kotani and V.Algazi,"Objective Picture Quality Scale (PQS) for Image Coding", Tech.Rep.CIPIC, University of California,Davis,1996

[15] Claudio M privitera, Lawrence W.stark, "Algorithms for Defining Visual Regions of Interest Comparison with Eye Fixation," IEEE trans on PAMI, Vol.22, No.9, pp.970-980,2000

[16] Wang Zhou, Bovik.A.C. "Wavelet-based foveated image quality measurement for region of interest image coding" Image Processing. Proceedings. Vol.2. pp.89 – 92, 2001

[17] Wang Kong-qiao,Shen Lan-sun,Xing Xin."A Quality Assessment Method of Image Based on Visual Interests". Journal of Image and Graphics. pp.300-303,2000.