X Congresso Brasileiro de Inteligência Computacional (CBIC'2011), 8 a 11 de Novembro de 2011, Fortaleza, Ceará

DETECTION OF POINTS FOR ROADS EXTRACTION IN AIRBORNE SAR IMAGES: AN APPROACH BASED IN SELF-ORGANIZING MAPS

Rodolfo G. Lotte[1], Cláudia M. de Almeida[2] e José Demísio S. da Silva[1]†
[1]Laboratory for Applied Mathematics and Computation - LAC
[2]Remote Sensing Division - DSR
National Institute of Space Research - INPE
rodolfo.lotte@inpe.br, almeida@dsr.inpe.br

Abstract – The great advantage in the utilization of radar images is the possibility of survering areas often covered by clouds, since the imaging by active sensors is independent of atmospheric conditions in the region of interest. Often, the mapping from these images is done manually, requiring considerable time and effort. This article discusses the use of Self-Organizing Maps - SOM as a method of identifying points in images. Each point represents an identified element belonging to a road. It will examine two different models to capture patterns in the image, presenting as a result both the identified points as well as the percentage of agreement in both models. The quality in the identification of these points is essential in the performance of certain roads extractors in digital images.

Keywords – radar images, computer vision, self-organizing maps, and road extraction.

1. INTRODUCTION

The use of radar (Radio Detection and Ranging) for ground pattern recognition and withdrawal of land information about changes in the target surface has been widely used in different application areas such as geology, hydrology, oceanography, cartography, and others. The operation of imaging radars is based on the transmission of microwaves in a certain range on the surface. The images are formed by the radiation emitted by the sensors and backscattered by objects. There are factors that are considered as obstacles in the formation of optical images. However, some of these factors are negligible in radar imaging, such as clouds, time of day, shadows caused by tall buildings and trees. Part of the energy emitted by the sensors is absorbed by the object, and the rest is backscattered. This energy is returned to the sensor and measure by it. This way, the image acquisition is possible at any time of day under any weather conditions, requiring only conducive overflight.

The radar imaging allow to help many areas of study, among these the geology in the analysis of cracks, foliation geological in the study of the prospecting and relief ground for the identification of areas with mineral resources etc. In hydrology, problems are treated as the management of water resources, the detection of soil moisture, flooding points. In oceanography, monitoring the sea, marine pollution caused by oil spills, detection of navigation in areas of illegal fishing, support for the establishment sea routes and identification of internal waves.

The process of extraction of roads is considered a very important component of the cartography [1]. The extraction roads can be used in some applications, such as automatic correction and updating of cartographic mapping. generally, two methods are used to obtain the road network. The first is performed by a team of experts who will field for the collection of information about the location and structure of roads, a process that takes time and effort. In the second method the extraction of roads is performed by means of remote sensing data from airborne or orbital. This second process can be categorized as manual, semiautomatic or automatic. The manual extraction implies a human operator to the delineation of roads, while the semi-automatic process requires human intervention to guide the process. And finally, the automatic process does not require human interference [2].

The extraction of linear features using imaging radar is still an open scientific question, and existing applications express different solutions. The extraction of linear features can be applied in areas such as cartographic mapping, the correction automatic or update products in geographic information systems (Geographic Information Systems - GIS) and others.

1.1 Previous Work

There are several currently available techniques for the extraction of roads. With the great availability of articles addressing the problem, there is a strong advance in the development of new methods in recent decades [1, 3, 4], both optical and radar images. Some of the previous works devoted are organized according to the methods of extraction. Given the large scope of available methods, this paper seeks to show the main contributions.

1. Automatic Seeding: The method of automatic seeding is used in some studies as a predecessor the extraction algorithm, ie it is not an extraction process, but a helper in the process itself. The technique is to identify points in the image, the location

of which characterizes the center of a road. Some methods require starting points as a starting point for the algorithm, such as the trackers road and active contour models (snakes). Harvey [5] highlights the importance of quality starting points for the performance of the algorithm extraction. Doucette et al. [1] presented the automatic seeding method using the parallel edge detection algorithm (Anti-parallel Centerline Extraction - ACE), in order to establish starting points for later start the roads routing process. The ACE method is the most popular approach for the automatic seeding, usually performed after the process of edge detection the image. Hu et al. [6] used the same process for the roads trackers.

2. Classification: The classification process is to categorize the data in the images into different classes of patterns, so that is assigned an identity or probability values for the data analyzed. The probability values indicate the probability that data belongs to a particular pattern class. Although the classifiers are used to categorize data, in imaging radar they are used as classifiers: spectral, textural, geometric, contextual and generators automatic class patterns [2]. Doucette et al. [7] used two classifiers typical for classifying digital images, they are the K-means methods and the Self-Organizing Maps (SOM). In this study, the authors using the classified image as the product of input in the acquisition of the centerlines through the algorithm SORM (Self-Organizing Map Road).

3. Hough Transform: Hough Transform (HT) is a mathematical operator can detect shapes in digital images, such as straight lines, circles and ellipses. Developed by Paul Hough in 1962 [8], became an important contribution in the computer vision area. The method consists of applying a transformation in the original image, such that all points belonging to the same segment to be mapped to a single point in the field of HT. The method is applied to a binary image, usually after the processing of identifiers edges. The transformation into the HT domain is expressed by $\rho = x\ cos\theta + y\ sin\theta$ where ρ represents the distance between a certain point on the line and the origin in xy-plane (imaginary line). θ is the angle between the axis y and the imaginary line. In Figure 1, we see that the transformation is performed such that each point in the xy-plane is converted in a sine wave in terms of HT, and thus the straight segment in the image can be interpreted by the maximum present in the field HT, ie, the intersections of the sine of each point on the line.

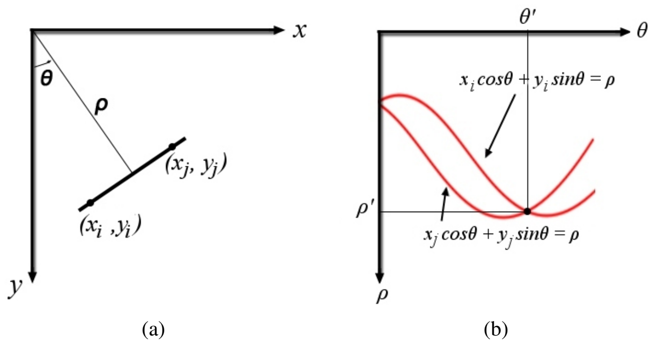


Figure 1: Parameterization of (ρ, θ): (a) In xy-plane (image plane). (b) In HT domain.
Source: Adapted from Gonzalez and Woods [9].

Being a very efficient operator in the detection of lines, the HT is widely used in solving the problem of extracting linear features in radar images. Dell'Acqua et al. [10] showed a variation of the algorithm in order to consider different widths for the features. In addition to reducing processing time, the algorithm provides better results by detecting the starting points and end of the straight segments instead of complete lines. The use of HT may also be applied to detect curves with low degree of curvature. Amberg et al. [11] used, in principle, the dynamic programming to extract the central axis of the tracks, then, the HT is used for connecting the discrete points from the extraction.

4. Mathematical morphology: mathematical morphology is used for a long time in digital imaging, and applications performed with morphological operators refer to the Set Theory. Processes such as union and intersection can be applied to images and are commonly used as filters in the stages of pre and post-processing. More complex operations involving effects of manipulating objects in the scene, such as dilation, erosion and others. The first allows you to increase the size of object, and the process of erosion, the opposite effect. Thus, operators are used, among many things, for the removal of small regions, holes and smoothing of shapes and contours. Idbraim et al. [12] used for morphological operators union of the results in a directional filter. Chanussot et al. [13] used this approach as a way of removing spurious passages in the image using, for example, the morphological opening operation and eliminating structures in darker relation to its environment, simplifying detection.

5. Roads trackers: The roads trackers process consists in plotting straight road between the points representing the location segments of interest. The algorithm has two basic stages: first, a function that determines the position of the next point, and following, a second function of refinement. At the end of the process, you get the complete network of roads, and then connecting lines represent the axis of the central features. Hu et al. [6] used the routing process based on the classification of "footprints" of the road. The process starts on the issues identified through the automatic seeding, and for each point is

determined the footprint. It is then analyzed to determine if its form is consistent with the ideal form of a road. Wiedemann and Ebner [14] using distance factors and assumptions to connect discontinuous segments.

6. Segmentation: The process of segmentation in digital images is the process of grouping data into subsets, with order to simplify the representation of the image and thus facilitate their review process. The output from this process is a set of regions or set of contours. The pixels belonging to the same set have similar characteristics, and each set differs significantly from its neighbors. Segmentation plays an important role in processing radar images. Some work as the main technique used in the extraction of roads [15, 16].

7. Active contours model (Snakes): It is an iterative and adaptive process for the identification of boundaries objects. The method, first developed by Kass et al. [17], consists of a polygonal curve embedded inside the object, which evolves in order to align the boundary. Snakes are used in the extraction of roads and the identification of the pathways centerlines in the images. Gruen and Li [4] an extension to the method used, which allows to extract the axes approach central pathways in optical images, eliminating barriers that often hinder such extraction, such as shadows caused by trees, vehicles, buildings etc. The original approach has many variations, among which stands out the method ribbon-snakes. Mayer et al. [18] used this process in high-resolution optical images to the acquisition of the edges parallel to the axis center, according to a constant pre-set width. The edges represent the roads between the border and background.

The purpose of this study is to discuss the method of seeding for the automatic identification of points that characterize the passage of a road in a SAR image, for which purpose the Self-Organizing Maps. Harvey [5] highlights the importance of quality points for a good performance of the extraction method. Will be address two ways to scan the image, and each one presents a distinct identification accuracy. However, it is necessary to evaluate the network parameters at each use, seeking minimize errors of commission and omission in identifying points of these models.

2. THE RADAR IMAGING

The basic geometry of formation of a airborne SAR image can be illustrated by Figure 2, where V determines the speed at which the platform moves in a certain direction, also known as the azimuth direction. The parameter H represents the altitude at which it lies. This platform carries a side dish with observation, which illuminates the surface study with pulses of electromagnetic radiation. The distance from the platform to the illuminated area is known as slant range R_0, and the distance from the Earth's surface on which the platform is (nadir) to the illuminated area is known as ground range, express by R_g in Figure 2 [19].

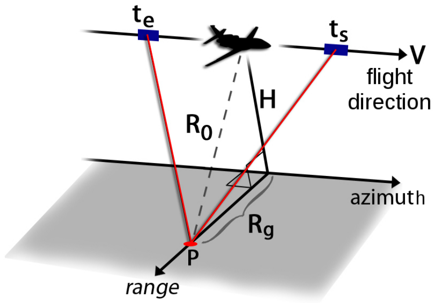


Figure 2: Geometry of airborne imaging radar target side.
Source: Adapted from Oliver and Quegan [19].

Typically, radar imaging systems have two types of platforms: aircraft or satellites. The imaging SAR by airborne platforms allows data acquisition at any time and anywhere on the Earth's surface, although it depends on weather conditions for the flyover. The satellites can view a larger area of the Earth's surface. By being continuously in orbit, is relatively easy to collect images of the same area in a systematic way to monitor changes in the biosphere.

Radar images are generated from the issuance of T_p pulse width in increments of T seconds. Using the model point fixed P, shown in Figure 2, the imaging system SAR has a time interval $(t_s - t_e)$, where t_e represents the point where the transmission is initiated by the wrist sensor, and t_s, the end point of transmission. In this range, the radar sends N pulses and collects N pulses resulting from the return of point P. The samples received are retained. during this interval, the platform moves $(t_s - t_e)$ meters with speed V. This range is known as synthetic aperture. The pulses received suffer frequency variations due to speed, and this effect is called Doppler effect [19].

The radar images obtained are characterized, in most cases, the speckle, noise due to the coherent nature radiation emitted in the formation of images. This noise is modeled as a multiplicative noise, varying in intensity according with the signal strength.

The noise is characterized by a grainy in SAR images, which often complicates the interpretation targets. In most cases, you must submit the image filtering routines to minimize noise or enhancement of the tracks, causing them to maximize the understanding of the areas to be extracted. Some extraction methods do not require the use of roads smoothing filters [4, 7], others, however, still require filtering [3, 10, 12].

3. AUTOMATIC SEEDING

As mentioned previously, the method of seeding is not necessarily an automatic extraction method, but a great helper in this process. It helps identify the points that characterize the road passing through the image. To this end, one will be used classification method using metrics in Artificial Intelligence (AI), which are characteristic to mimic, computationally, human behavior and learning. The method called Self-Organizing Maps will be addressed in the next section.

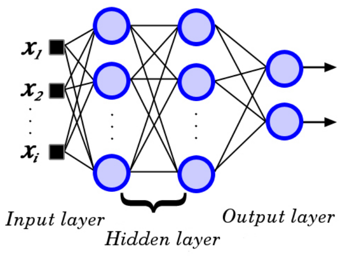
3.1 Self-Organizing Maps

One of the first mathematical models to simulate human learning was developed in 1943 by Warren McCulloch and Walter Pitts [20], and consisted of a set of information processing units, called neurons, or node, interconnected, simulating a neural network. Later, in 1958, this model was extended by Rosenblatt [21, 22] and called Perceptron network. Consisted of only one input layer and one output. Because of this structure, its use was limited to solving only linearly separable problems. These limitations meant that the perceptron network gain another layer of neurons, a intermediate layer. Thus, this model enabled the resolution of complex problems (Figure 3a).

Later, in 1982, came the Self-Organizing Maps, or simply SOM, which is based on unsupervised learning, where is not necessary to submit data to the network for their learning. The activation of neurons, is held in a process "competition " between them. In the literature, the SOM networks are used mostly as an agent classifier data. They are also called Kohonen maps, referring to its creator Teuvo Kohonen [23]. The Kohonen's network has no intermediate layer, and its architecture consists of only one input layer and one output, being the latter represents the map of neurons (Figure 3b). Learning occurs by obtaining the location of the neuron on the map, that is, their cartesian coordinates on the map. This process is carried out, resulting in the neuron with the lowest value according to the standard Euclidean (Equation 1).

$$i(l, c) = min||X - W_j|| \tag{1}$$

Where $||.||$ denotes the Euclidean norm between the input values X, W_j, the weights corresponding to each neuron j and i describes the winner neuron with coordinates l, c in map [24].



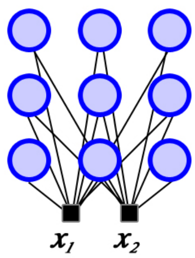
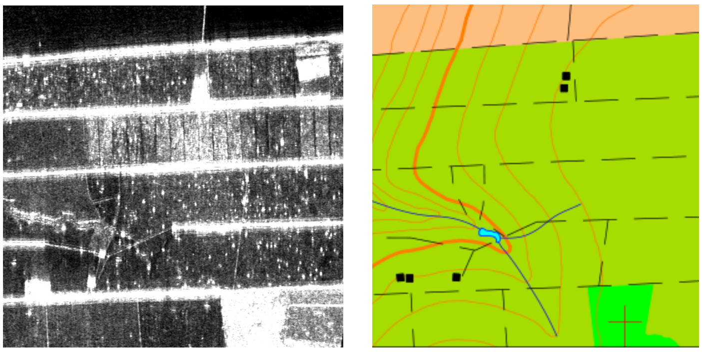


Figure 3: Artificial neural network architecture (a) MLP with two hidden layers. (b) Two-dimensional SOM
Source: Adapted from Haykin [24].

4. RESULTS

4.1 Data used

For the experiments of both methods, we adopted a cut-out SAR image (513x513 pixels) covering the region of Paragominas in Para State, with radiometric resolution of 8 bits and 2.5 meters of space in the band P. The image was acquired with the sensor OrbiSAR aerial survey in the period between February 11, 2007 and March 13, 2007, at an altitude of 11,000 m (Figure 4). All routines implementation and the experiments were performed in environment MATLAB version 7.8.0.347.



(a) (b)

Figure 4: Picture used in the experiments: (a) Cut-out the SAR image (Band P). (b) Reference mapping. Source: Orbisat [25].

4.2 Results

As this paper aims to identify roads in SAR images, and these are often characterized by clearer profiles than their surroundings, the training patterns were then defined. The Figure 5 shows a representation of the patterns of road-oriented 45°. In SAR images, the roads are not always found with profiles clearer, however, the roads in the used image are comprised with this profile. Thus, the ANN was trained to recognize only this type. The orientation of a road image is an unknown information, and thus were created eight different orientations profile. However, that the network is more robust, the training is presenting one more pattern, it represents what is not road, totaling nine input patterns. For the window of each pattern was defined the size of 19x19 pixels. By convention, the data of each pattern were aligned in a vector, so that became a pattern one-dimensional, defining the network architecture with 361 input and output layer as a two-dimensional map of variable size.

0	0	0	0	0	0	0	0	0	0	31	63	93	125	155	187	217	250	255
0	0	0	0	0	0	0	0	0	31	63	93	125	155	187	217	250	255	250
0	0	0	0	0	0	0	0	31	63	93	125	155	187	217	250	255	250	217
0	0	0	0	0	0	0	31	63	93	125	155	187	217	250	255	250	217	187
0	0	0	0	0	0	31	63	93	125	155	187	217	250	255	250	217	187	155
0	0	0	0	0	31	63	93	125	155	187	217	250	255	250	217	187	155	125
0	0	0	0	31	63	93	125	155	187	217	250	255	250	217	187	155	125	93
0	0	0	31	63	93	125	155	187	217	250	255	250	217	187	155	125	93	63
0	0	31	63	93	125	155	187	217	250	255	250	217	187	155	125	93	63	31
0	31	63	93	125	155	187	217	250	255	250	217	187	155	125	93	63	31	0
31	63	93	125	155	187	217	250	255	250	217	187	155	125	93	63	31	0	0
63	93	125	155	187	217	250	255	250	217	187	155	125	93	63	31	0	0	0
93	125	155	187	217	250	255	250	217	187	155	125	93	63	31	0	0	0	0
125	155	187	217	250	255	250	217	187	155	125	93	63	31	0	0	0	0	0
155	187	217	250	255	250	217	187	155	125	93	63	31	0	0	0	0	0	0
187	217	250	255	250	217	187	155	125	93	63	31	0	0	0	0	0	0	0
217	250	255	250	217	187	155	125	93	63	31	0	0	0	0	0	0	0	0
250	255	250	217	187	155	125	93	63	31	0	0	0	0	0	0	0	0	0
255	250	217	187	155	125	93	63	31	0	0	0	0	0	0	0	0	0	0

(a)

(b)

Figure 5: Training pattern with orientation of 45°: (a) with 19x19 matrix of intensity values in gray levels, representing a clear road. (b) Representation of (a).

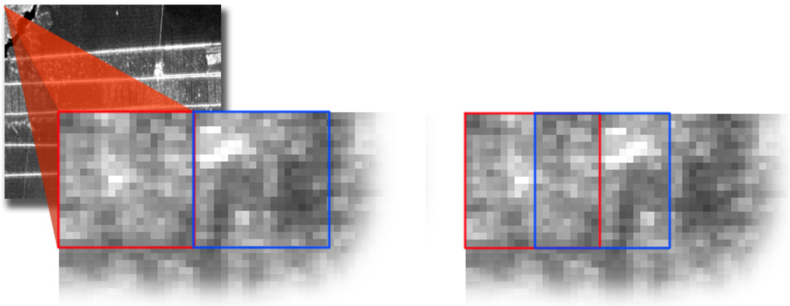
After training the network, the next step is the pattern recognition, the first reading of the values of each pixel. This was read as follows: a grid is established the same size as the training patterns, so convoluted that it is in the image jumps predefined. The values assigned to each quadrant is read as an input to the network. Have been developed two different ways to capture data in the image: full pattern and interleaved pattern. The Figure 6 illustrates how the process is performed in readings between two patterns. The red lattice features the pixels of the first pattern and the blue grid, the second pattern, both sweeping the scene entirely.

The points that characterize the passage of a road were marked according to the Euclidean distance between the winner neuron (the its pattern shown) and each center of the eight patterns that characterize a road. If the distance does not exceed a certain threshold, the central pixel of this pattern is then flagged as belonging to a road. For each type of filtering, was a suitable threshold value, and this value enables decreasing the identification of falses points that can exist between models.

Observing Table 1, the results from the processing show that the percentage of hits decreases as the map the network of neurons, although the learning rate is higher. In Figure 7, the results are shown presented the best identifications.

5. CONCLUSION

This paper presented the use of self-organizing maps as an approach in the automatic seeding of roads in an airborne SAR image. The results shown indicate efficient use of SOM as a data classifier, and thus a good method in the automatic seeding of roads in radar images. The identification process was performed without the need for any pre-processing image such as smoothing and enhancement filters. The tests were performed on the image original with extension *tiff*, and the final results shown in



(a) (b)

Figure 6: Models filter used for reading the values of pixels: (a) Full pattern model. (b) Interleaved pattern model.

Table 1: Identification of points: Percentages of hits and misses.

	Experiment	Map	Rate	Epochs	Threshold	Hits	Misses
Full pattern	1	60x60	0.05	1,500	240	63%	37%
	2	60x60	0.05	1,500	260	68%	32%
	3	60x60	0.05	1,500	280	73%	27%
	4	40x40	0.35	1,500	110	23%	77%
	5	40x40	0.35	1,500	120	49%	51%
	6	40x40	0.35	1,500	130	36%	66%
Interleaved pattern	1	60x60	0.05	1,500	240	63%	37%
	2	60x60	0.05	1,500	260	56%	44%
	3	60x60	0.05	1,500	280	53%	47%
	4	40x40	0.35	1,500	110	42%	68%
	5	40x40	0.35	1,500	120	35%	65%
	6	40x40	0.35	1,500	130	15%	85%

the standard *jpg*.

From the results presented, it is evident that the interleaved pattern model behaves with more precision over another, this occurs in view of the size of your shift at every step of reading the pixels in the process of convolution. However, many spurious points are flagged, causing errors of commission in large quantities. One solution to this would be the creation of a pruning algorithm, which would facilitate the choice of the best points among those identified, eliminating the other. In the full pattern model some places tend not to be identified in the center of the road due to the large displacement of the grid, ie, the higher the shift, the greater the probability of not getting the point on the way, and the lower the probability of identification. Both models captures have a very large rate of errors in the face of the characteristics of the SAR image. This behavior is considered normal, since it was not carried out any pre-processing the image.

If increased the accuracy of the model, for example, a pixel-to-pixel model, surely it would increase the number points identified, although it also increased the likelihood of identifying isolated or false segments, ie, the higher the shift of the grid convolution, the greater the chance of identification of continuous segments of interest. On the other hand, it also increases the chance of "jump " on a road and therefore does not recognize it.

REFERENCES

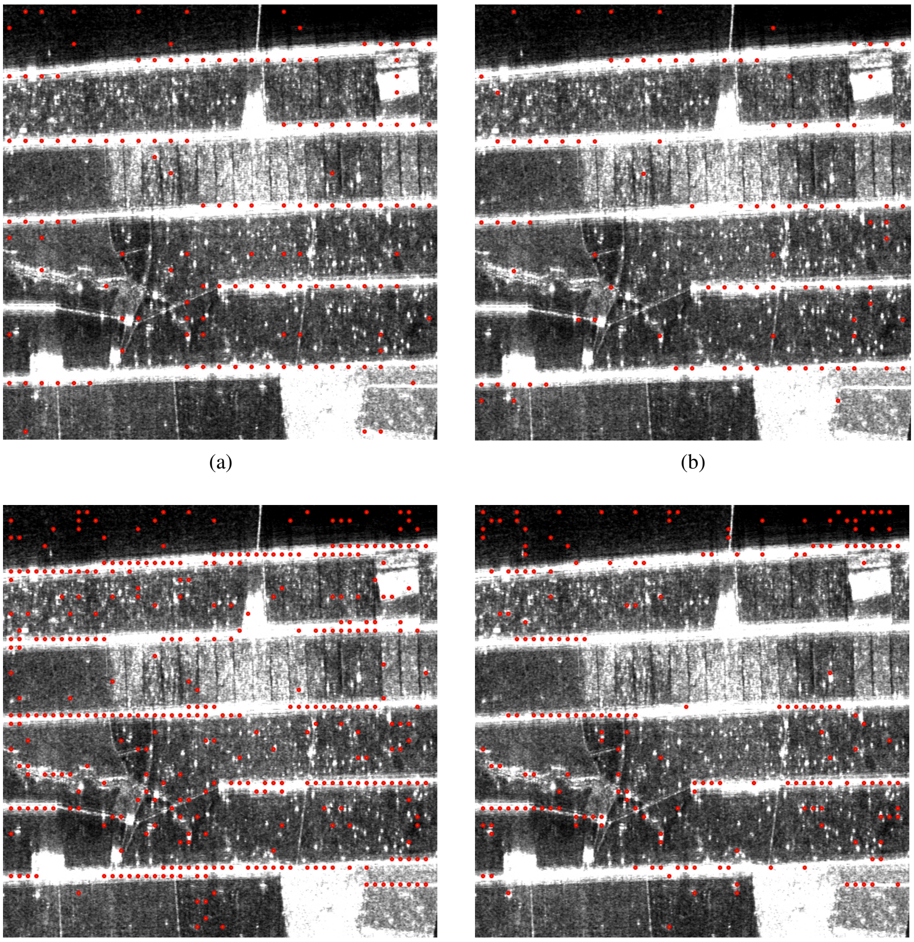
[1] P. Doucette, P. Agouris and A. Stefanidis. "Automated road extraction from high resolution multispectral imagery". *Photogrammetric engineering and remote sensing*, vol. 70, no. 12, pp. 1405–1416, Dezembro 2004.

[2] A. C. Hauptfleisch. "Automatic road network extraction from high resolution satellite imagery using spectral classification methods". Master's thesis, University of Pretoria, Fevereiro 2010.

[3] F. Tupin, H. Maître, J.-F. Mangin, J.-M. Nicolas and E. Pechersky. "Detection of linear features in SAR images: Application to road network extraction". *IEEE Transactions on Geoscience and Remote Sensing*, vol. 36, no. 2, pp. 434–453, Março 1998.

[4] A. Gruen and L. H. "Semi-automatic linear feature extraction by dynamic programming and LSB-Snakes". *Photogrammetric engineering and remote sensing*, vol. 63, no. 8, pp. 985–995, 1997.

[5] W. A. Harvey. "Performance evaluation for road extraction". *In Proceedings of the ISPRS Workshop on 3D Geospatial Data Production: Meeting Application Requirements*, 1999.



(a) (b)

(c) (d)

Figure 7: Results of full pattern and interleaved pattern, (Table 1): (a) Experiment 2 - full pattern. (b) Experiment 3 - full pattern. (c) Experiment 1 - interleaved pattern. (d) Experiment 2 - interleaved pattern.

[6] J. Hu, A. Razdan, J. Femiani, M. Cui and P. Wonka. "Road network extraction and intersection detection from aerial images by tracking road footprints". *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 12, pp. 4144–4156, 2007.

[7] P. Doucette, P. Agouris, A. Stefanidis and M. Musavi. "Self-organised clustering for road extraction in classified imagery". *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 55, pp. 347–358, Fevereiro 2001.

[8] P. V. C. Hough. "Method and means for recognizing complex patterns". *United States Patent*, , no. 3069654, 1962.

[9] R. C. Gonzalez and R. E. Woods. *Digital Image Processing (3rd Edition)*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 2008.

[10] F. Dell'Acqua and P. Gamba. "Detection of urban Structures in SAR images by robust fuzzy clustering algorithms: the example of street tracking". *IEEE Transactions on Geoscience and Remote Sensing*, vol. 39, no. 10, Outobro 2001.

[11] V. Amberg, M. Coulon, P. Marthon and M. Spigai. "Structure extraction from high resolution SAR data on urban areas". *In Proceedings of IEEE International Geoscience and Remote Sensing Symposium*, vol. 3, pp. 1784–1787, Setembro 2004.

[12] S. Idbraim, D. Mammass, D. Aboutajdine and D. Ducrot. "An automatic system for urban road extraction from satellite and aerial images". *WSEAS Trans. Sig. Proc.*, vol. 4, pp. 563–572, October 2008.

[13] J. Chanussot, G. Mauris and P. Lambert. "Fuzzy Fusion Techniques for Linear Features Detection in Multitemporal SAR Images". *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, no. 3, Maio 1999.

[14] C. Wiedemann and H. Ebner. "Automatic Completion and Evaluation of Road Networks". *International Archives of Photogrammetry and Remote Sensing*, vol. XXXIII, no. B3, 2000.

[15] C. Zhang. "Towards an operational system for automated updating of road databases by integration of imagery and geodata". *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 58, pp. 166–186, 2004.

[16] J. B. Mena and J. A. Malpica. "An automatic method for road extraction in rural and semi-urban areas starting from high resolution multi-spectral satellite imagery". *Pattern Recognition Letters*, vol. 26, pp. 1201–1220, 2005.

[17] M. Kass, A. Witkin and D. Terzopoulos. "Snakes: Active Contour Models". *Internetional Journal of Computer Vision*, vol. 1, no. 4, pp. 321–331, 1987.

[18] H. Mayer, I. Laptev, A. Baumgartner and C. Steger. "Automatic road extraction based on multi-scale modeling, context, and snakes". *International Archives of Photogrammetry and Remote Sensing*, vol. XXXII, no. Part-3-2W3, pp. 106–113, 1997.

[19] C. Oliver and S. Quegan. *Understanding Synthetic Aperture Radar Images*. Artech House Publishers, Boston, 1998.

[20] W. McCulloch and W. Pitts. "A logical calculus of the ideas immanent in nervous activity". *Bulletin of Mathematical Biophysics*, vol. 5, pp. 115–133, 1943.

[21] F. Rosenblatt. "The Perceptron: A probabilistic model for information storage and organization in the brain". *Psychological Review*, vol. 65, pp. 386–408, 1958.

[22] F. Rosenblatt. *Principles of Neurodynamics*. Spartan Books, Washington, DC, 1962.

[23] T. Kohonen. "Self-organized formation of topologically correct feature maps". *Biological Cybernetics*, vol. 43, pp. 59–69, 1982a.

[24] S. Haykin. *Neural Network: A Comprehensive Foundation*. Macmillan College Publishing Company, 1994.

[25] "ORBISAT DA AMAZÔNIA IND. E AEROLEVANTAMENTO S.A." Imagem da cidade de Paragominas (PA) e entorno 2007. Imagem de radar de abertura sintética aerotransportado. Sensor OrbiSAR. Aquisição entre 11 fev. 2007 e 13 mar. 2007. Bandas X e P. CD-ROM, 2010.