AUTOMATIC EXTRACTION OF RIVERS IN SATELLITE IMAGES USING GEOMETRIC ACTIVE CONTOURS

Rodrigo Bruno ZANIN[1,2]
Erico Fernando de Oliveira MARTINS[1,2]
Aluir Porfírio DAL POZ[2]

Abstract

This work aims to define and test a method for the extraction of rivers in orbital images for regions that are seasonally flooded, ie, large areas containing more water bodies besides the river, such as Pantanal. In the proposed methodology, several tools from the area of Image Analysis and Computer Vision have been employed, performing a preprocessing, followed by a topological modeling that is built upon a skeletonization process followed by an analysis of this skeleton. Lastly, the methodology selects structure that represents the river, by performing a topological filtering. This process is responsible for the selection of points that initiate the process of delineation of rivers using a geometric active contour method, called "Level Set Method". The methodology was evaluated qualitatively (visual) and quantitatively (numerical) using the criteria of completeness and correctness in a series of real images of the Pantanal region. The edges extracted from rivers, were projected onto the original images, thus allowing a qualitative assessment. With respect to the numerical results for the criteria of completeness and correctness, these were always above 80%, which shows that the methodology is very effective and robust for the community that needs to perform feature extraction in remote sensing images.

Key-words: Feature extraction. Topological modeling. Extraction of rivers. Skeletonization. Level set

[1] Universidade do Estado de Mato Grosso – UNEMAT – Dep. Matemática – Sinop - Av. dos Ingás, 3001 – Centro - 78 550 - 000 – Sinop – MT, Brasil – E-mails: {rodrigo.zanin , prof_erico}@unemat-net.br

[2] Universidade Estadual Paulista – UNESP – PPGCC – Presidente Prudente - Rua Roberto Simonsen, 305 – Centro Educacional - 19 060 - 900 – Presidente Prudente – SP, Brasil – E-mail: aluir@fct.unesp.br

Resumo

Extração automática de rios em imagens orbitais utilizando contornos ativos geométricos

O presente trabalho tem como objetivo definir e testar uma metodologia de extração de rios em imagens orbitais para regiões que sejam alagáveis sazonalmente, ou seja, regiões que contenham mais corpos d'água além do rio a ser extraído, tais como o Pantanal. Na metodologia proposta, várias ferramentas da área de Análise de Imagens e Visão Computacional têm sido empregadas, realizando um pré-processamento, seguido de uma modelagem topológica que é construída em cima de um processo de esqueletização seguido de uma análise desse esqueleto. Por fim, a metodologia seleciona a estrutura que representa o rio, realizando uma filtragem topológica. Esse processo é responsável pela seleção dos pontos que iniciam o processo de delineamento dos rios utilizando um método de contorno ativo geométrico, denominado *"Level Set Method"*. A metodologia foi avaliada qualitativamente (visual) e quantitativamente (numérica) utilizando os critérios de completeza e correção, em um conjunto de imagens reais da região do Pantanal. As bordas dos rios extraídas foram projetados sobre as imagens originais, permitindo assim uma avaliação qualitativa. No que tange os resultados numéricos para os critérios de completeza e correção, estes sempre foram superior a 80%, o que mostra que a metodologia é bastante eficiente e robusta para a comunidade que necessita realizar extração de feições em imagens de Sensoriamento Remoto.

Palavras-chave: Extração de feições. Modelagem topológica. Extração de rios. Esqueletização. Level set.

INTRODUCTION

Currently, the use of satellite or aerial images is the main source of information for generating and updating cartographic and topographic data (MENA, 2003). In that sense, automatic extraction of features in digital images, such as that of Remote Sensing, is a topic of great interest in Geosciences. Thus the work related to extracting cartographic features is found in several areas such as Digital Image Processing and Computer Vision.

The cartographic features are usually related to the presence of protrusions in digital images, such as rivers, lakes and/or roads (QUACKENBUSH, 2004). Classical examples of feature extraction are found in the methods used for road extraction in digital images (DAL POZ et al., 2005), the extraction of rivers being an application that deserves considerable attention, especially in large areas of vegetation (DILLABAUGH et al., 2002;GRASSINI; SOILLE, 2007).

Poullis and You (2010) draw attention to the fact that with technological advancement and cost reduction, images have become increasingly popular, expanding their applications to various areas. However, data interpretation and analysis still remains a difficult task and its manual realization is a reality in most applications.

In a broader sense, feature extraction, in particular the features defined as linear have various applications in Computer Vision; and have received considerable attention in the literature (DAL POZ; ZANIN, 2005). Many techniques for the extraction of linear features have been proposed in the literature. They are usually classified as automatic and semi-automatic and, operator intervention in the extraction process is the criteria for this classification (LACOSTE et al., 2005).

Methods based only on the spectral response of targets of interest, that is based only on the intensity attribute, such as binarization methods or classification techniques, typically have limited success nowadays due to the complexity of the scenes (DILLABAUGH et al. , 2002). This complexity generates a large ambiguity in the intensity of the pixels (primary attribute), since pixels belonging to the same object may suffer considerable variation, while pixels belonging to different objects may have similar values. This can occur due to various problems related to the system's sensor taken from the scene.

In view of these difficulties, the more consolidated research in Image Analysis performs two basic steps which are: detections of features that result both in the features of interest and the false positives that arise from protrusions in the images such as holes that can be caused by shadows and / or cars on the roads and boats or misclassification in the case of rivers; the second step is the refinement of the results that occurs based on a priori knowledge of the feature of interest, this knowledge is spatial and / or spectral (SAMUEL et al., 2012). These steps are defined as pre-processing and post-processing.

Regarding the objective of this work, which is the extraction of rivers, Soile et al. (2007) propose a model for extraction that exploits topological and geometrical characteristics of rivers by relying on these attributes to rebuild the mesh hydrographic present in satellite images. This model is based on a watershed segmentation followed by using mathematical morphology techniques for extracting rivers.

Shah et al. (2011) proposed a methodology for extracting river in orbital images based on a k-cluster medium in an RGB image processed with specific histograms for each channel. It is noteworthy that in these studies the classification is the main step, since the detection of water bodies in orbital images based on classification processes is a tool established in literature (NATH; DED, 2011).

Tin et al. (2012) developed a method for the extraction of rivers in satellite images of high resolution, based on the feature detection set to "corners" (features with high value of curvature) and then applied a filtering based on texture selecting the rivers in the orbital images.

However, the methods used for detection and extraction of the rivers mentioned, perform the extraction, in most cases, of water bodies. This work does not generate good results for seasonally flooded areas as is the case in Pantanal that at certain times has plenty of water bodies (GALDINO et al. 2006).

In this context a methodology to extract only rivers, separating them from other water bodies is important for research linked to the use and land cover of this biome that is so characteristic.

Thus, the aim of this work is to propose and test a methodology for extracting rivers from orbital images of flooded regions, such as the Brazilian Pantanal. To achieve this goal, the work was divided into four sections: the first to make a brief introduction; the second to propose a methodology; the third to evaluate it; and the fourth to present the main conclusions

PROPOSED METHODOLOGY

The proposed methodology is based on the three steps shown in the flowchart in figure 1. These steps are: Pre-processing, Topological Modeling and Extraction of Rivers. The steps are explained in the following sections.

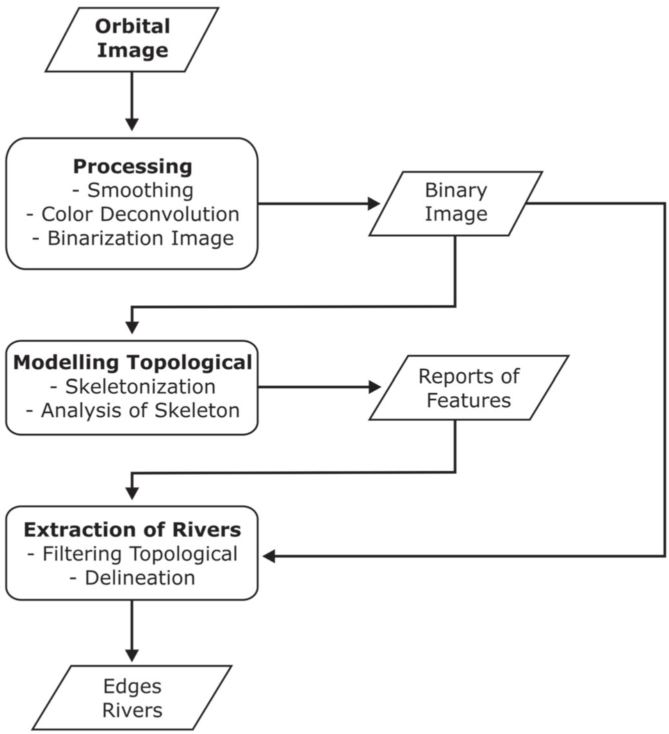


Figure 1 - Flowchart of the proposed methodology

Preprocessing

The preprocessing step aims to transform an input image (original image) into a binary image containing the features of interest separated from the background, allowing the process of topological modeling of the region which is the next step of the methodology.

To achieve this goal, preprocessing is divided into three sub-steps which are: smoothing, color deconvolution and binarization.

Smoothing

The smoothing process aims at reducing the noise present in the image. Nevertheless, noise can be generated by different causes and is a very common problem in digital images, so the problem cannot be corrected in the source image, just minimized with this processing. From a practical point of view, the noise causes two pixels which correspond to the same intensity in the scene having different gray levels in the image.

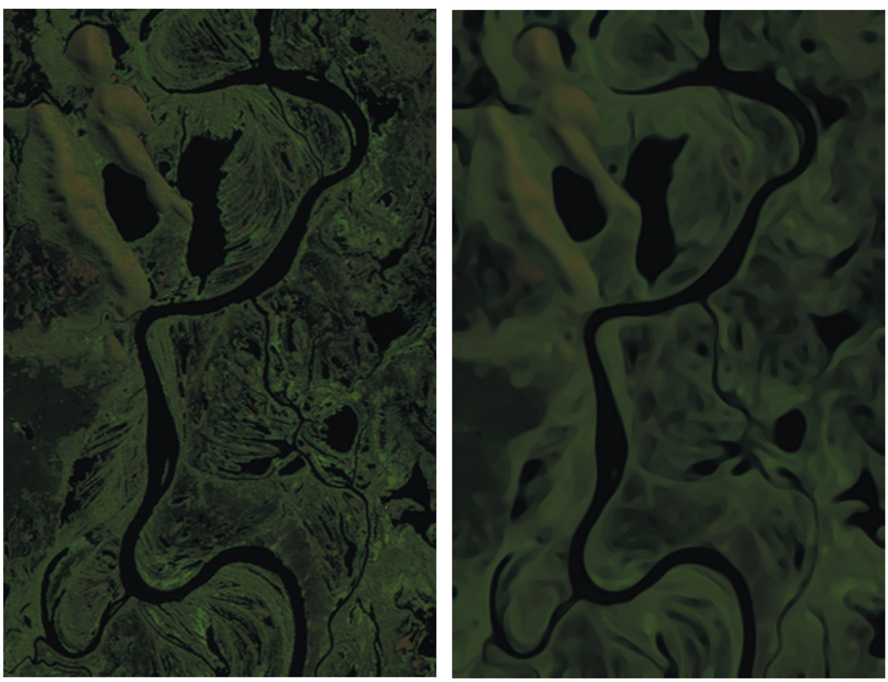
Several techniques have been proposed in the literature to remove or minimize the noise in digital images. Among them there are those who are focused on Partial Differential Equations (PDE), and have received large membership area Image Analysis. The basic idea in image processing with EDP is, according to Barcelos (2002), to modify the image with EDP obtaining the expected results as the solution of the differential equation.

The images used in this work are scene clippings collected from Landsat 5 TM with a spatial resolution of 30m (low-resolution) in flooded areas. The regions contains several water bodies which are the features that become tend are more evident in the image after the smoothing process.

The smoothing algorithm used in the method is the anisotropic diffusion which was proposed by Perona and Malik (1990). In this algorithm the image is treated as a two-dimensional function *u*(*x,y*) and an EDP is applied upon it as indicated by equation 01.

$$u_t = div[g(|\nabla u|^2, c)\nabla u] \tag{01}$$

This EDP (equation 01), *div* is the divergence operator and ∇u is the gradient of the function with initial values $u = u_0$ defined by the original image at the initial time t_0. The method uses *n* iterations in a grid with defined length by the parameters of the algorithm. The most important parameter in this algorithm is the level of smoothing that is defined in terms of the standard deviation of solution's kernel of the EDP shown in equation 01 (Gaussian kernel). The result of this process can be seen in figure 2.



(a) (b)

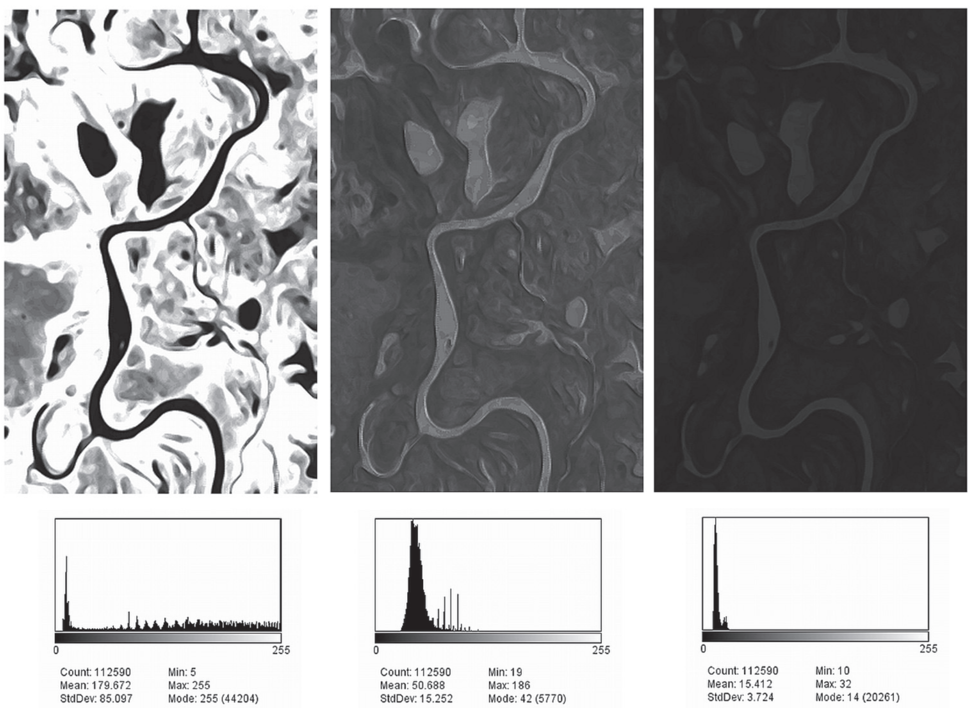
Figure 2 - (a) Cropping the image in the original form, (b) image smoothed by anisotropic diffusion algorithm of Perona and Malik (1990)

Color Deconvolution

After the smoothing process (Figure 2), only the most relevant bodies of water tend to remain in the image due to its low resolution characteristic. Thus, the next step of the methodology is to apply a color deconvolution algorithm that aims to separate a certain range of color intensity (RUIFROK; JOHNSTON, 2001).

The color deconvolution algorithm was originally developed for the area of microscopy and aims to separate the image regions, whose tracks from intensities are predominant, creating calls, image indices. The process according to Ruifrok and Johnston (2001) using an input array that can be defined by the mean values for each channel (RGB) in the regions used as samples for forest areas, green areas and areas of water bodies.

The result of applying the color deconvolution process proposed by Ruifrok and Johnston (2001) for the test image in figure 2(b) is shown in figure 3. In this figure the indice images represent the result from color deconvolution algorithm, with their respective histograms. In the third component it is possible to verify the bimodal characteristic of the histogram in this image (Figure 3 (c)). This characteristic is a result of a more effective contribution of the green component in RGB composition, isolating bodies of water more efficiently.



(a) (b) (c)

Figure 3 - Results of the deconvolution of color to the images smoothed with their respective histograms. (a) Component 01, (b) Component 02 (c) Component 03

Binarization Image

The last step in the pre-processing stage is the image binarization process, since the next stage of the methodology is applied in a binary image. Considering that the resulting image of the deconvolution color presents a bimodal histogram (Figure 3 (c)), the proposed methodology uses a consecrated algorithm of the area Image Analysis for binarization of the region. This algorithm is known as the Otsu method (OTSU, 1979) and uses an optimization of the equations of discriminate analysis to define an optimal threshold T.

As intensity, measured in shades of gray at a pixel coordinate (x, y) in the image is defined by I(x, y), the process of binarization is accomplished comparing all the pixels of image with the T value, generating a binary image L(x, y) defined by:

$$L(x,y) = \begin{cases} 255 \text{ if } I(x,y) > T \\ 0 \text{ if } I(x,y) \le T \end{cases} \qquad (02)$$

The threshold T, calculated by Otsu (1979) has, as theoretical assumption, the best results for images that have bimodal histograms. The result of applying Otsu's binarization (OTSU 1979), for example to the image in figure 3(c) can be seen in figure 4(a).

Topological Modelling

The second step of the proposed method is the topological modelling of the region of interest which in this case is represented by the binary image. This step is also divided into two sub-steps, which are skeletonized and the skeleton analyzed, generating in the end, a report with the main characteristics of the features which in this case, are bodies of water present in the image. These reports are defined as reports of the features. The sub-steps for topological modelling are explained below.

Skeletonization

According to Pedrini and Schwartz (2008), one of the basic problems for the development of efficient systems in the area of Image Analysis is the selection of features needed to be extracted from the object of interest. Accordingly, after the pre-processing step that results in a binary image, the objects will be represented and described in formats suitable for subsequent processes.

Based on the need to obtain a compact representation of the features and the result obtained in the pre-processing, the method applies a skeletonization algorithm proposed by Blum (1967), called the Medial Axis Transform (MAT). This algorithm calculates the set points that are the closest to both edges of the object simultaneously, a property known as double tangency.

The result of the skeletonization process is the skeleton of the region, which defines representations of various bodies of water present in the image of the region. An example of this process can be seen in figure 4(b), which shows the skeleton of the region representing the various water bodies.

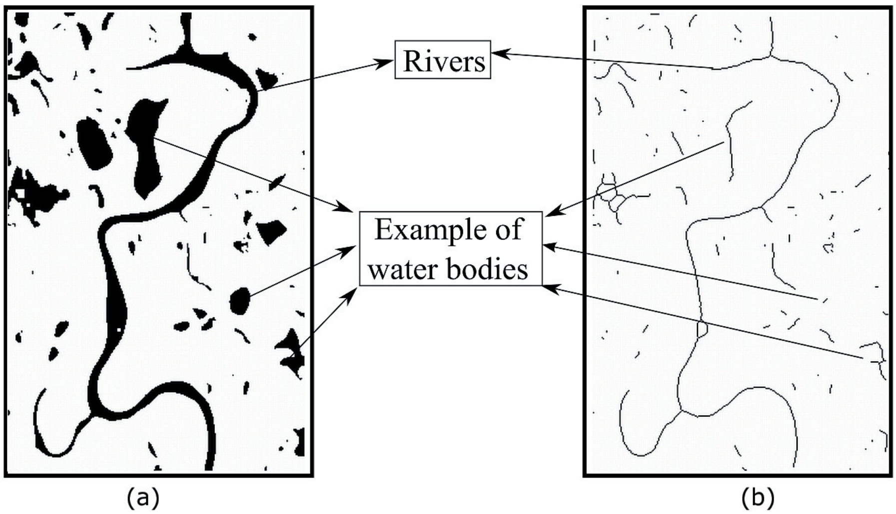


Figure 4 - Results of Binarization (Otsu, 1979) and skeletonization (Medial Axis Transform) with examples of water bodies and rivers. (a) Binary image, (b) Skeleton of the region

Analysis of Skeleton

The skeleton resulting from the previous stage is an image with no semantic features. In practice, what we have are black pixels representing the skeleton on a white background. Thus, the semantic features of the region will be assigned through a process defined as analysis of the skeleton, creating a model with topological characteristics of the region. This model will receive the denomination of topological model, created due to the process of analyzing the skeleton.

The analysis of skeleton is based on the dot properties that make up the skeleton (Figure 5 (b)). Thus, the model uses points defined as points of interest; these points are labeled as end points and crossing points, besides the interior points of the skeleton. The labels of the points are defined in the algorithm that performs the Medial Axis Transform following the rules proposed by Di Ruberto (2004). These rules define a pixel formally as the terminal point, point of intersection or interior point as follows:

- Definition 1 -A skeleton pixel is defined as a terminal pixel when it has just one pixel in its vicinity.
- Definition 2 –A skeleton pixel is defined as the crossing pixel when it has, more than two pixels in its neighborhood.
- Definition 3 –A skeleton pixel is defined as the pixel inside the “branch” if, in addition to it, there are only two pixels in its neighborhood.

Based on the labeled pixels, a topological model is created hierarchically as shown in table 01. In this model the pixels labeled as interior points, terminals or junction, form the most basic level of the hierarchical structure shown in table 1(a). The intermediate level is composed by a set of connected pixels and limited by points of interest (end points or points of intersections), forming branches or arms of the skeleton, these being indicated by the coordinates of its start point (P_i) and its end point (P_f), as shown in table 1(b). Branches or arms that are limited by points of interest, have either of the following configurations: terminal - terminal, terminal - crossing or intersection - intersection.

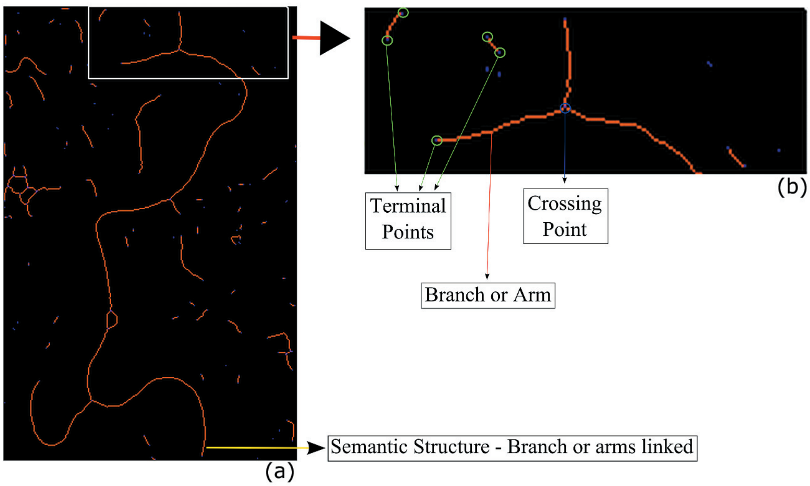


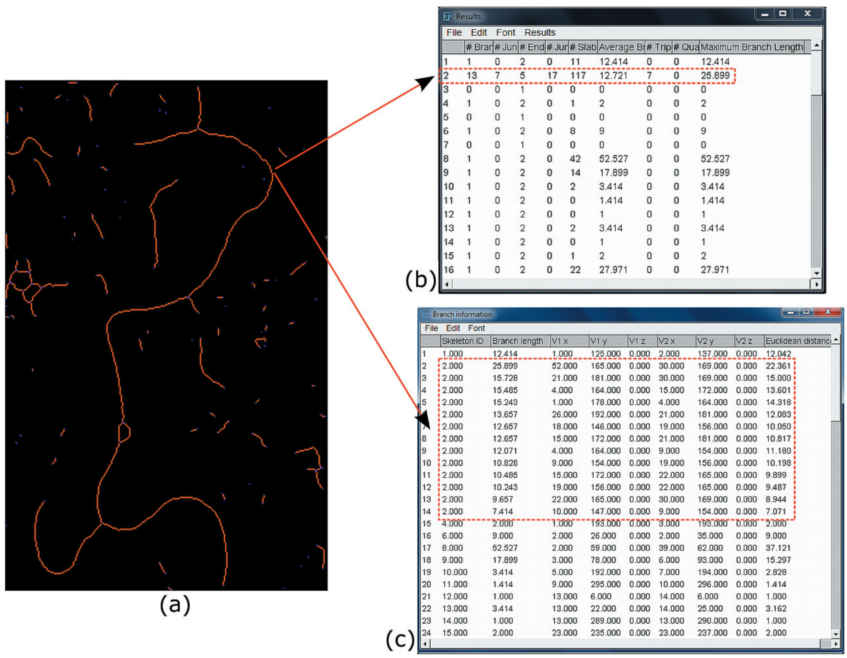
Figure 5 - Labeled Skeleton. (a) Labeled Skeleton, (b) Example of Points of Interest (end points and crossing points), defining the Arms or Branches and Semantic Structure

Finally, the last level of the hierarchical structure, which generates the model used in the next step are semantic structures (E_n), which are formed by sets of n arms or branches connected together, as shown in table 1 (c).

Table 1 - Hierarchical Structure of topological model created with their representations, features and hierarchical levels (a - c)

Representation	Feature	Hierarchical Level	
Labeled Point (x,y)	- Interior Point - End Point - Crossing Point	- Basic Level	(a)
Branch or Arm (P_i,P_f)	- A set of connected pixels and limited by points of interest (Final or Crossing points)	- Intermediate Level	(b)
Semantic Structure $E_n = \{(P_{1i}, P_{1f}, \ldots,(P_{ni}, P_{nf})\}$	- Set Ramos or Arms linked together.	- Semantic Level	(c)

Late in the process the models are defined as topological numerical files, called reports of features. These reports contain the pixel coordinates of the points of interest that make up the branches or arms and the identification of the branches or arms if they are linked, forming semantic structures. An example of this report to the image of figure 5(a) is shown in figure 6. In this figure it is possible to see in the report the lengths of each of the arms or branches that make up semantic structure bounded by a dashed box (Figure 06 (b, c)).



	# Bran	# Jun	# End	# Jun	# Slab	Average Br	# Trip	# Qua	Maximum Branch Length
1	1	0	2	0	11	12.414	0	0	12.414
2	13	7	5	17	117	12.721	7	0	25.899
3	0	0	1	0	0	0	0	0	0
4	1	0	2	0	1	2	0	0	2
5	0	0	1	0	0	0	0	0	0
6	1	0	2	0	8	9	0	0	9
7	0	0	1	0	0	0	0	0	0
8	1	0	2	0	42	52.527	0	0	52.527
9	1	0	2	0	14	17.899	0	0	17.899
10	1	0	2	0	2	3.414	0	0	3.414
11	1	0	2	0	0	1.414	0	0	1.414
12	1	0	2	0	0	1	0	0	1
13	1	0	2	0	2	3.414	0	0	3.414
14	1	0	2	0	0	1	0	0	1
15	1	0	2	0	1	2	0	0	2
16	1	0	2	0	22	27.971	0	0	27.971

	Skeleton ID	Branch length	V1 x	V1 y	V1 z	V2 x	V2 y	V2 z	Euclidean distanc
1	1.000	12.414	1.000	125.000	0.000	2.000	137.000	0.000	12.042
2	2.000	25.899	52.000	165.000	0.000	30.000	169.000	0.000	22.361
3	2.000	15.728	21.000	181.000	0.000	30.000	169.000	0.000	15.000
4	2.000	15.485	4.000	164.000	0.000	15.000	172.000	0.000	13.601
5	2.000	15.243	1.000	178.000	0.000	4.000	164.000	0.000	14.318
6	2.000	13.657	26.000	192.000	0.000	21.000	181.000	0.000	12.083
7	2.000	12.657	18.000	146.000	0.000	19.000	156.000	0.000	10.050
8	2.000	12.657	15.000	172.000	0.000	21.000	181.000	0.000	10.817
9	2.000	12.071	4.000	164.000	0.000	9.000	154.000	0.000	11.180
10	2.000	10.828	9.000	154.000	0.000	19.000	156.000	0.000	10.198
11	2.000	10.485	15.000	172.000	0.000	22.000	165.000	0.000	9.899
12	2.000	10.243	19.000	156.000	0.000	22.000	165.000	0.000	9.487
13	2.000	9.657	22.000	165.000	0.000	30.000	169.000	0.000	8.944
14	2.000	7.414	10.000	147.000	0.000	9.000	154.000	0.000	7.071
15	4.000	2.000	1.000	193.000	0.000	3.000	193.000	0.000	2.000
16	6.000	9.000	2.000	26.000	0.000	2.000	35.000	0.000	9.000
17	8.000	52.527	2.000	59.000	0.000	39.000	62.000	0.000	37.121
18	9.000	17.899	3.000	78.000	0.000	6.000	93.000	0.000	15.297
19	10.000	3.414	5.000	192.000	0.000	7.000	194.000	0.000	2.828
20	11.000	1.414	9.000	295.000	0.000	10.000	296.000	0.000	1.414
21	12.000	1.000	13.000	6.000	0.000	14.000	6.000	0.000	1.000
22	13.000	3.414	13.000	22.000	0.000	14.000	25.000	0.000	3.162
23	14.000	1.000	13.000	289.000	0.000	13.000	290.000	0.000	1.000
24	15.000	2.000	23.000	235.000	0.000	23.000	237.000	0.000	2.000

Figure 6 - Example of the reports of the features (topological model for semantic structures) present in the image. (a) Image of Labeled Skeleton, (b) Report of the general features, (c) Report by feature with properties of each branch or arm

Extraction of Rivers

The last step of the methodology proposed in this work is the extraction of the feature of actual interest, which in this case are the rivers that make up the region of the flooded areas (Pantanal). The process of feature extraction Image Analysis, is divided into detecting the feature of interest and its delineation. Usually these processes generate a file with information in vector form containing the pixel coordinates of the feature. The representation of the feature can be given by its edges, its interior or the union of both. In this paper such sub-steps occur in the topological filter which performs detection and in the delineation of the borders of rivers. These sub-steps are described below.

Topological Filtering

Based on the model built in the previous section, organized in the form of reports (reports of features), the goal of this step is to select among the semantic structures the one that represents the river in the picture. To achieve this goal, the process performs a topological filtering among semantic structures present in the image (water bodies) defining among them the largest structures. This filtering is performed based on geometric characteristics of rivers, i.e. the filtering uses context injunctions.

$$C_i = \sum_{j=1}^{n} b\_length_j \tag{03}$$

Wherein C_i is the length of the i-th semantic structure and it is calculated as the sum of the lengths of the *n* arms or branches (b_length_j) that comprise the *i-th* semantic structure. This calculation is carried out based on data from the reports of features indicated in figure 6 (c).

The result of topological filtering, defined in the methodology, is the structure with more length (greatest C_i). However, the proposed method uses only the points of interest selected from the semantic structure, i.e. the terminal points and points of intersections. These points are used as starting points in the delineation process of the feature detected in this case, the rivers that make up the region.

Delineation

The last step of the extraction process is the delineation of the river that occurs in the binary image, this process is carried out using the selected structure as a base in topological filtering.

The algorithm for the delineation proposed in this work is the Level Set Method (LSM). This algorithm is a process defined as a geometric active contour and was developed by Osher and Sethian (1988).

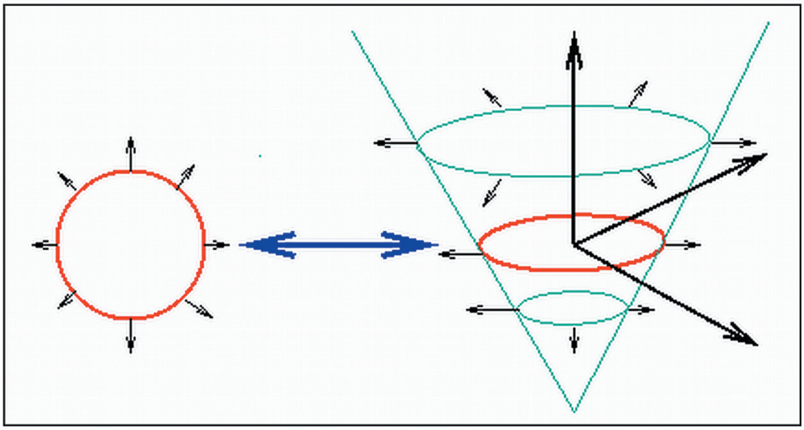
According to Osher and Sethian (1988) one of the main advantages of the LSM, is that this algorithm is a numerical technique that simulates the motion of curves and/or surfaces generated in a digital image, allowing the representation of the feature of Interest which can be described as a curve. This representation is what facilitates the applications of numerical techniques that simulate the evolution of the curves (Figure 7 (a)). The evolution occurs on a Cartesian grid, obviating the need for a parameterization of these curves. This approach is defined as Eulerian, generating geometric active contour (Osher and Sethian, 1988).

The LSM is, according to Osher and Sethian (1988), a very robust technique for delineation of shape that suffer large topological changes, and its choice is defined according to the characteristics of rivers in satellite images. The application of LSM is based on a G closed curve, containing the edges of the feature and an auxiliary function φ, known as function of the level curve, which is calculated for each of the levels. The curve at zero Γ is represented by: $\Gamma = \{(x,y) \mid \varphi(x,y) = 0\}$.

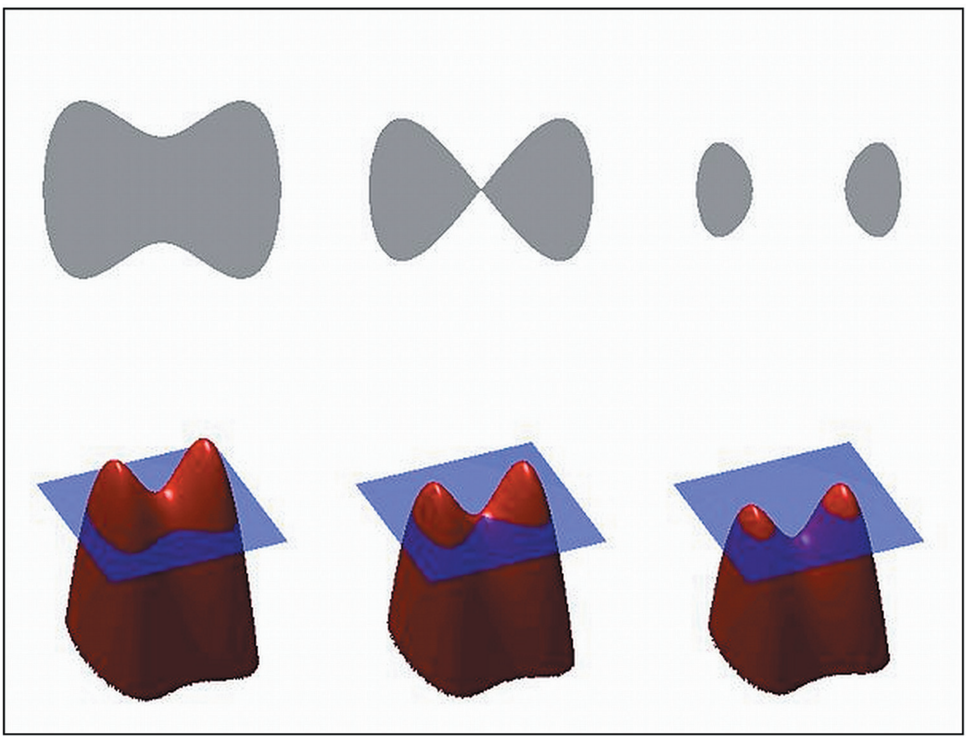
Considering that the motion of the curve Γ is in its normal direction with a speed *v*, so the evolution of the curve 04 must satisfy the equation defined by

$$\frac{\partial \varphi}{\partial t} = v \mid \nabla \varphi \mid \tag{04}$$

This equation is a Partial Differential Equation (PDE) particularly of Hamilton-Jacobi, whose numerical solution is performed using the finite differences on a cartesian grid (OSHER; SETHIAN, 1988). In practice LSM requires at least an initial point which is set as a seed point to initialize the delineation process. However, the proposed method uses as seed points, all points of interest from the semantic structure, selected in the topological filtering, making the method more robust.



(a)



(b)

Figure 7 - Level Set Method for Digital Images (Osher and Sethian, 1988)

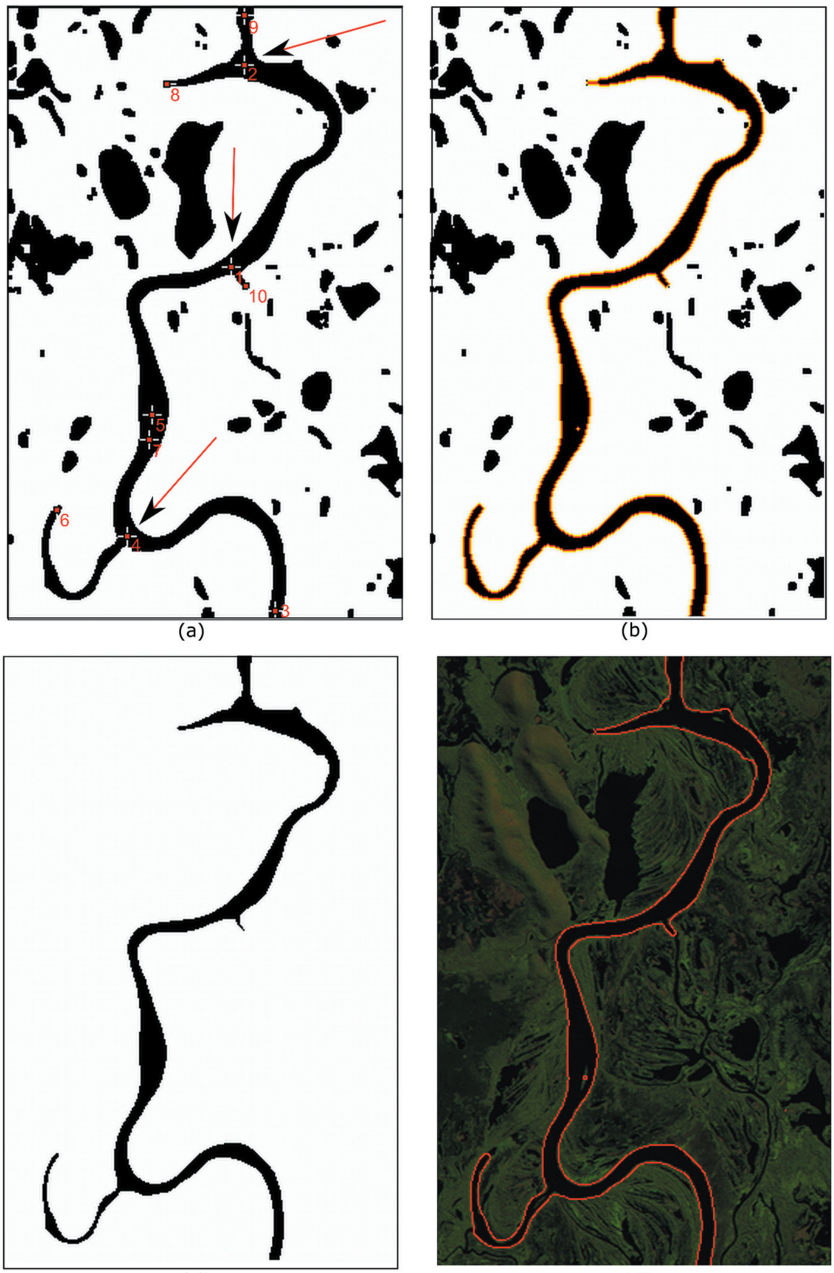


Figure 8 - Application of Level Set Method (LSM). (a) Binary image with seed points, (b) Evolution of LSM (c) Rio outlined by LSM (d) River Edges projected on the original image

The result of applying the LSM can be seen in figure 8. Figure 8(a) shows the seed points and Figure 08(b) the evolution of the algorithm. The resultant delineation is the image of figure 8 (c) whose edges have been superimposed on the original image, as shown in figure 8(d), enabling a visual assessment of the process.

The image used to present the methodology (Figure 2 (a)) composes the set which consists of five images with regions of the Wetland with rivers, selected to evaluate the proposed methodology.

RESULTS

In this work two evaluations were conducted, one quantitative and the other qualitative, overlapping vectors extracted over the original image. The quantitative one uses the applications of two quantitative criteria, comparing the results obtained by the method with extractions performed by the operator taken as references.

To exemplify the criteria, figure 9 shows the reference feature indicated by the gray color with its area indicated by A_R, whereas the extracted feature is indicated by the white color with its area defined by A_E and, finally, the intersection between the two features indicated by the red color has its area represented by $A_{R \cap E}$.

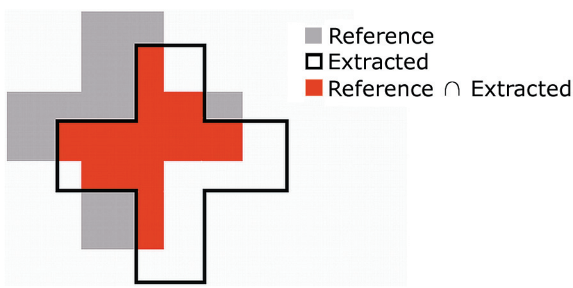


Figure 9 - Representation of the reference feature, the extracted feature and the intersection between the reference and extracted features

Based on the extracted and reference features, the criteria used for quantitative evaluation (numerical) are the measures of completeness C_{comp} and correctness C_{corr} (DAL POZ et al., 2005). In this work, these measures are defined by:

Completeness - is the ratio of the area of intersection between the features and the area of feature used as reference, as indicated in Equation 05;

$$C_{comp} = \frac{A_{E \cap R}}{A_R}.100\% \qquad (05)$$

Correctness: it is the ratio of the area of intersection of the features and the area of feature extracted by the methodology, as shown in Equation 06.

$$C_{corr} = \frac{A_{E \cap R}}{A_E}.100\% \qquad (06)$$

In addition to the image used in the methodology (Figure 2 (a)), other four images were selected to evaluate it. These images are shown in figure 10 (a - d) whose degrees of difficulty are quite different, since they all contain several water bodies in the region besides the river to be extracted.

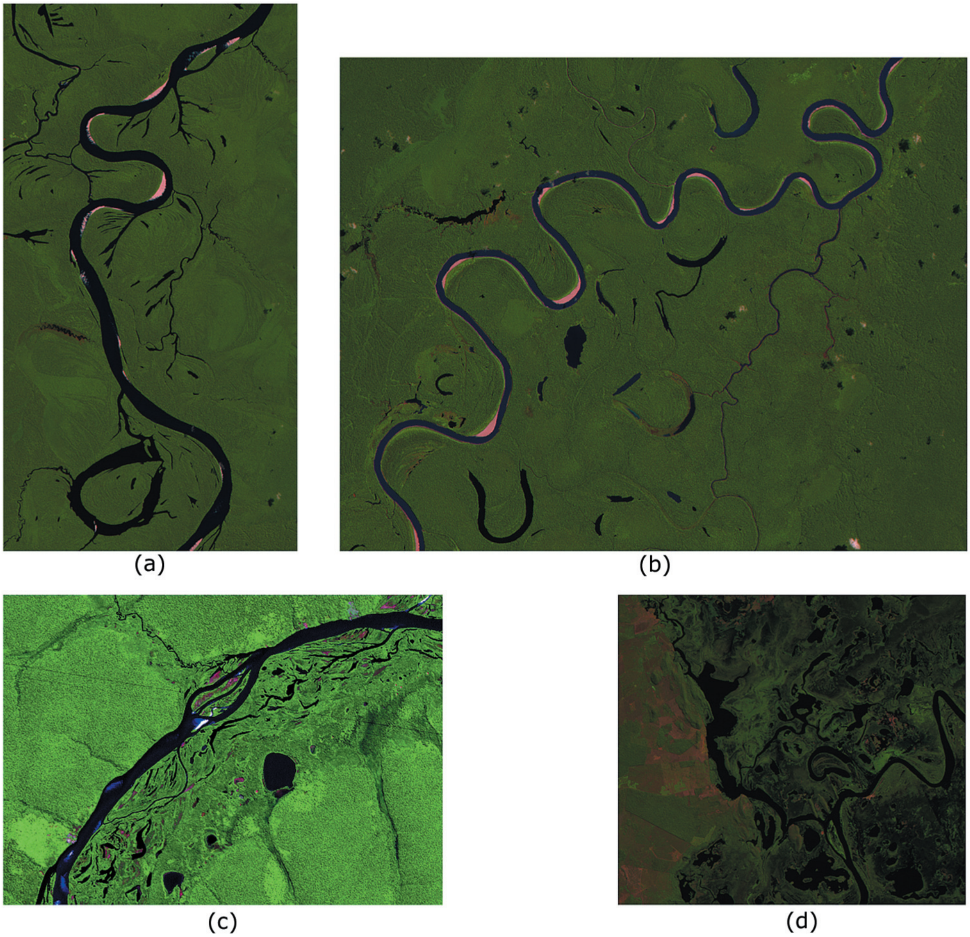


Figure 10 - (a - d) Selected images to evaluate the proposed methodology

The results of the pre-processing with the respective skeletons of the images used for testing the methodology are shown in figure 11 (a - d). This figure shows the importance of the pre-processing step once the binary image resulting from the preprocessing should contain only the bodies of water. The figure also allows visualizing the importance of the skeletonization process, because in skeleton of the region the largest structure is, usually, the one that represents the river.

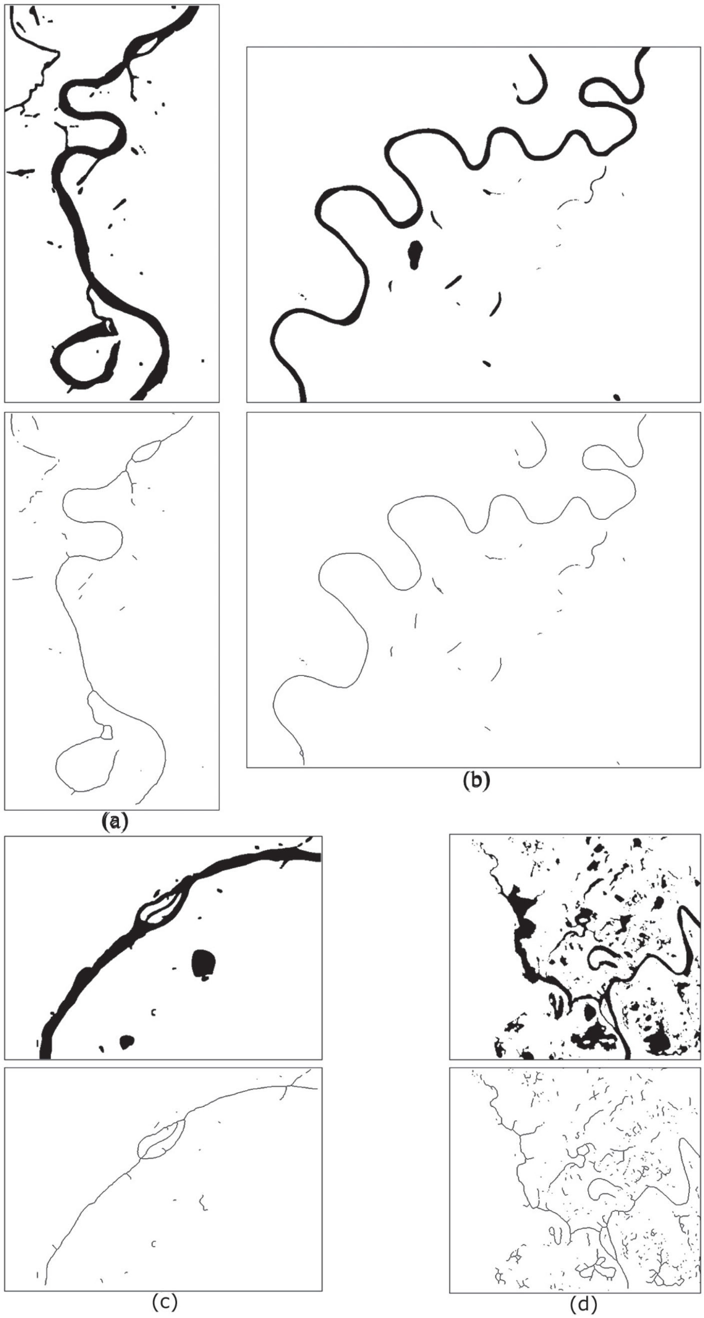


Figure 11 - Results for the pre-processing step with their skeletons calculated for the test image (a - d)

Considering that the methodology proposed in this work is to extract only rivers in flooded areas, it outperforms the traditional classification methods used for detection of water bodies in orbital images, as can be seen in figure 12 (a - d). This figure shows the features extracted in a binary image containing only the river, which was isolated from other water bodies.

In figure 12 (a - h), the extracted river edges were projected on the original images, showing the feasibility and efficiency of the proposed methodology according to the qualitative evaluation (visual). The results of the quantitative evaluation (numeric) for criteria of completeness C_{comp} and correctness C_{corr} (equations 05 and 06) are shown in table 2.

Table 2 - Quantitative results for the criteria of completeness and correctness of the five selected images to evaluate the methodology

Experiment	*Area - Ref*	*Area - Ext*	*Area - Int*	*Completeness*	*Correctness*
Image 01	6959	6934	6912	99,32%	99,68%
Image 02	34215	34211	34132	99,76%	99,77%
Image 03	22535	22152	19575	86,86%	88,37%
Image 04	21885	17982	17765	81,17%	98,79%
Image 05	11914	12020	11749	98,62%	97,75%

The results show the efficiency of the methodology in the extraction of rivers in general. However, some specific aspects considered relevant can be cited. These aspects are:

- Selection of the rivers among bodies of water that have similar characteristics to the rivers with respect to its width, as shown in figure 12(b). This is a result of the parameterization of length along the skeleton of the region.
- Selection of the rivers among bodies of water that have proportional lengths but different widths as shown in figure 12(a). This result is one of the benefits of the delineation model, namely the Level Set Method.
- Selection of the rivers among the various bodies of water present in the image in general. This positive characteristic of the methodology is a result of the proposed model for rivers with a linear feature when compared to other bodies of water. The result of this characteristic is shown in the examples of figures 12(c, d).

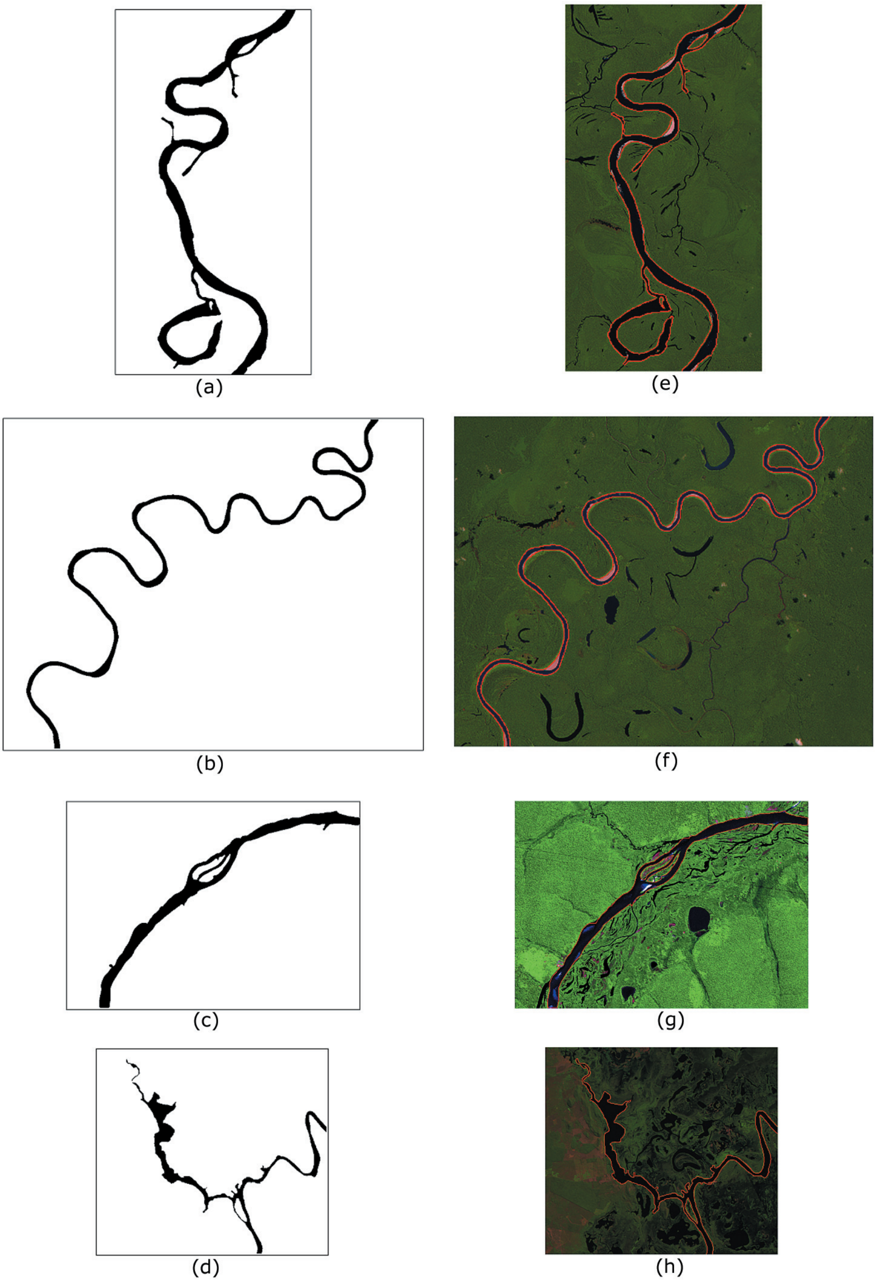


Figure 12 - Results of the methodology for test images of Figure 10 (a - d). (a - d) Rivers selected among various water bodies (e - h) River edges extracted and projected in red on the original images

CONCLUSIONS

This paper proposed a methodology for extracting rivers from orbital images based on geometric active contours, which proved to be robust when considering the obtained qualitative and quantitative (visual and numerical) results.

The proposed methodology can be considered useful both for research in the area of Image Analysis that has feature extraction as one of its main objectives, as well as for the research related to information extraction in Remote Sensing images since they use the features extracted automatically or semi-automatically into digital images for assigning them semantic characteristics.

The relevance of this work for the area of Image Analysis is directly linked to the toolkit of Digital Image Processing that is used for the extraction of rivers. This process can be defined as a contextual extraction because it uses specific characteristics of the feature of interest as injunctions in order to define the set of procedures for extraction, which in this case are the rivers in satellite images.

The proposed method also shows the interdisciplinary nature of the work and of the area of Images Analysis which has applications in several fields of knowledge.

In relation to the relevance of this work with the scientific community, which uses Remote Sensing to extract information, it proposes to create and test a methodology that is capable of extracting (detect and delineate) only rivers in flooded regions (Pantanal) isolating them from other bodies of water present in the image.

In this sense the images used to test the methodology and results obtained for the criteria of completeness and correctness, show the efficiency of the process. This can be useful for researchers who need information only of the rivers in the context of the regions flooded with several bodies of water.

The limitations of the proposed methodology are directly related to the limitations of the techniques of Digital Image Processing used, such as smoothing, color deconvolution and skeletonization, for example.Thus some of the future prospects for this work are: the expansion of the methodology to images from other sensors with different spatial and spectral resolutions to overcome the limitations related to the stage of pre-processing, the possibility to add additional information such as Infra-Red to improve the segmentation process of water bodies, as well as information from the object space (3D) to improve topological modeling and filtering of elements of interest, among other that primarily manage information redundancy to be used in the proposed methodology.

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