IOSR Journal of Engineering (IOSRJEN) www.iosrjen.org
ISSN (e): 2250-3021, ISSN (p): 2278-8719
Vol. 10, Issue 4, April 2020, ||Series -I|| PP 32-43

Semiautomatic Method for Reconstruction of Road Network Detected from Satellites Image

Raíssa Souza[a]; Samara Azevedo[b]; Guilherme Cardim[a]; Erivaldo Antonio da Silva[a]*; Maurício Dias[a]; Wallace Casaca[c]

[a]São Paulo State University (UNESP), Faculty of Science and Technology, Presidente Prudente-SP, Brazil, 19060-900

[b]Federal University of Itajubá (UNIFEI), Natural Resources Department, Itajubá-MG, Brazil, 37500-903

[c]São Paulo State University (UNESP), Rosana's Experimental Campus, Rosana-SP, Brazil, 19274-000

Received 25 March 2020; Accepted 14 April 2020

ABSTRACT: The extraction of curvilinear features of road networks in digital images from Remote Sensing (RS) is very important for Cartography, because this extraction contributes to updating cartographic products. As different curvilinear features of a road network present in the same image usually have distinct characteristics, a single method or technique can extract features precisely in one area of the image, but only partially in another area of the same image. Consequently, features extraction methods usually present results with failures, compromising the quality of the extraction of the curvilinear features of the road network in the image as a whole. Aiming at presenting an alternative to improve the results from the extraction of road network in digital images, this paper proposes a semiautomatic method for post-processing digital images from remote sensing in order to reconstruct curvilinear features of road network extracted with flaws. The method uses techniques such as active contour, regression, and cubic splines for the reconstruction of curvilinear features in road networks, which were only partially extracted in previous processing. According to the proposed method, each technique is applied alone or jointly to parts of an image that have flaws, since each type of flaw is better reconstructed by one or another reconstruction technique. The results achieved by this work, which were validated by an increase of almost 10% in the completeness, correctness, and quality metrics of the extraction after its reconstruction, allowing cartographic products to be updated with higher accuracy.

Keywords: Feature reconstruction, regression, cubic splines, active contour.

I. INTRODUCTION

The extraction of road network features present in digital images from Remote Sensing (RS) has attracted the attention of the scientific community for decades. The processes of extracting features of road network from aerial or orbital digital images have been widely used and are important for many applications, such as urban planning, geographic database updating, and change detection (WANG et al. al., 2016). These processes aim at identifying targets present on the terrestrial surface to provide cartographic updates. However, despite the variability and quantity of studies already published by the scientific community, such processes are still subject to failures in cartographic features extraction.

The development of automatic and semiautomatic methodologies that perform the extraction of spatial features has increased, especially the extraction of road networks, which among the anthropic features, has significant importance in everyday human activities (MABOUDI et al., 2017). Among the activities that demand updated and accurate road network data are traffic management, navigation, tourism, emergency and rescue services, etc. (Mayer et al., 2006; RAVANBAKHSH et al., 2008).

Approaches for extracting road networks have been found in the literature for more than 40 years, and among the various methods published, most use neural networks (BARSI et al., 2002), mathematical morphology (COURTRAI and SÉBASTIEN, 2016; CARDIM et al., 2017), graphs (UNSALAN and SIRMACEK, 2012), snakes and dynamic programming (GRÜEN et al., 1999), and object-based methods (MABOUDI et al., 2017). In addition, methods that integrate other sources of data have also been developed, such as using Laser data (SOILÁN et al., 2018).

Although a number of solutions have been proposed, depending on the approach and type of data employed, the result of the extraction may have only partially extracted features. This is because road network extraction is a problem in the scope of object recognition from images, aggravated by factors such as the characteristics of the image itself (spatial and spectral resolution, lighting conditions and soil characteristics); the complexity of the scene; and the variability of the objects present in the image (WANG et al., 2016). For example, there are methods targeted for extraction of road networks in low and medium spatial resolution images, which are prone to failure when applied to high resolution images since the volume of information to be processed (pixels) is larger and therefore unsuitable for large areas. The result is the incomplete identification of the contours of the targets of interest, which reduces the quality of the extraction produced.

For the cases in which the extraction of features presents flaws, increasing quality depends on the use of techniques for reconstruction of these features. Among the techniques used for feature reconstruction of road networks, three deserve to be highlighted for their high performance: active contours snakes (PETERI et al., 2003), regression (SIRONI et al., 2016), and cubic splines (WU et al., 2009).

Active contours are based on borders, so it detects the border and separates the image into region and border. Snakes are deformable active contours (Kass et al., 1987), and are intended to approximate the locations and shapes at the borders since it is assumed that the borders are continuous and smooth (BERTUOL, 2007). The technique consists of adapting the initial curve drawn around or inside the object by means of subsequent iterations that adapt the curve to the edge of the object, minimizing a given energy (JUNIOR SILVA, 2010). The parametric representation of a snake is $v(s) = (x(s), y(s))$, where x and y are functions that represent coordinates and $s \in [0,1]$ is the domain. The application of active contours snakes for the reconstruction of curvilinear features of road network extracted with flaws can be found in Peteri et al., 2003. In that study, the active contours were combined with multi-resolution analysis based on wavelet transform for edge detection at multiple resolutions and reconstruction of road networks, which had already been extracted by a preprocessing phase.

The regression technique explores the relationship between dependent variables, response values, independent variables, and exploratory values. Regression is used as a curve fit or, in other words, an adjustment of flaws at the edge of the images. The behavior of Y in relation to X can be presented in a variety of forms such as cubic, linear, and exponential, among others. The application of regression for the reconstruction of curvilinear features of road network extracted with flaws can be found in SIRONI et al., 2016. In that study, regression was applied by reformulating the detection of multi-scale central lines to solve irregularities in the linear structures and the difficult to distinguish central lines in relation to the neighborhood. Among several applications found in that study, there is the regression applied to the reconstruction of features with road networks extracted with flaws, present in high-resolution satellite images.

On the other hand, there are techniques focused on interpolation of polynomials, and when those polynomials are of high order, it is possible to detect bad behaviors while determining the result. The Cubic Splines technique is one of the methods that assists in eliminating these behaviors. In addition to solving the bad behavior of polynomials with high orders, cubic splines can be used both in extraction and reconstruction of features (GALO et al., 2001; OLIVEIRA, 2003). The application of cubic splines for the reconstruction of curvilinear features of road network extracted with flaws can be found in WU et al., 2009. This study presents a strategy for the extraction and reconstruction of road networks. The study focuses on the prediction of positioning and the width of tracks of roads. In that work, cubic splines are used to reconstruct the geometry of the roads, mainly related to curves. Images with different lighting conditions are considered.

The higher the quality in the extraction of the features and the reconstruction, the greater the final precision obtained. Therefore, with the objective of presenting an alternative to improve the results from the extraction of road network in digital images, this article proposes a semi-automatic method of post-processing of remote sensing digital images for the reconstruction of curvilinear features of road network using techniques such as active contour, regression, and cubic splines.

II. MATERIALS AND METHOD

To evaluate the proposed semi-automatic method of post-processing, this method was applied to a dataset composed by real RS images, which allowed us to investigate curvilinear features of road network with different characteristics. All experiments applied the method to verify if it is able to reconstruct curvilinear features extracted with flaws, independent of the different characteristics presented by the curvilinear road network features of the RS digital images found in the dataset. Each experiment applied, semi-automatically, the three techniques of active contouring, regression, and cubic splines, to reconstruct curvilinear features of road network that were only partially extracted in previous processing. The experiments aimed to verify if the proposed method is an alternative to improve results from the extraction of road network in digital images. The images present in the dataset of digital images used in this research present diverse scenarios. They correspond to different stretches of road networks that range from, the Rodoanel highway in the capital of São Paulo, Brazil, the Tamoios highway near the coast and mountain range, and unpaved rural roads. All images from the dataset are from RS and were obtained by sensors aboard the QuickBird satellite, in the case of Rodoanel highway, and WorldView2, in the case of Tamoios highway. The images were collected by sensors at different times, ranging from March 26, 2009 to August 14, 2015.

These images were carefully chosen to be used in the experiments of this research for three different reasons. The first reason is because they all have high spatial resolution (50 cm in the panchromatic band) and 16-bit radiometric resolution, although they originate from different sensors. The second is because they have curvilinear features of road networks with very different characteristics (e.g. paved and unpaved; different textures and colorations in their pavements; different lighting conditions; the presence or absence of vehicles; or being partially covered by different elements such as viaducts, shadows, trees, etc.). The more characteristics a curvilinear feature presents in the same image, the greater the likelihood of finding failures in the extraction of the feature from that image. Therefore, the use of this set of images was important because it allows evaluation of the robustness of the method for reconstruction of curvilinear features with flaws taking in consideration a diversity of characteristics.

The final reason these images were selected is because they present three distinct levels of difficulty that can be related to the reconstruction of curvilinear features of road networks: low, medium, and high sinuosity. The higher the sinuousness of the curvilinear features, the more difficult it is to be reconstructed. Figure 1 presents examples of images from the dataset used to evaluate the semiautomatic method of post-processing proposed in this research. The images show the three different levels of difficulty related to reconstruction: low sinuosity in Figure 1 (a), mean sinuosity in Figure 1 (b), and high sinuosity in Figure 1 (c).

Using this set of images was important because it allows evaluation the robustness of the application of the techniques for reconstruction of the features (active contours, regression and cubic splines), while taking in consideration the different levels of difficulty related to reconstruction of curvilinear features of road networks extracted with flaws.

Based on previous descriptions, it is noted that the experiments tried to evaluate the ability of the method to reconstruct curvilinear features extracted with flaws, taking into account different contexts and degrees of difficulty related to road networks. Therefore, the experiments considered: (1) problems with low complexity (for example, a single flaw related to the presence of a viaduct in a curvilinear feature with low sinuosity, as shown in Figure 2 (a) original and (b) pre-processed for extraction of road network features); (2) problems with medium complexity (for example, flaws related to the presence of vehicles and differences in pavement, which result in intensity variation in the image, in a curvilinear feature with medium sinuosity, as shown in Figure 3 (a) original and (b) pre-processed for extraction of road network features); and (3) problems with high complexity (for example, flaws related to the absence of road paving and the presence of shadows, trees, undergrowth, spots, etc., in a curvilinear feature with high sinuosity, as shown in Figure 4 (a) original and (b) preprocessed for extraction of road network features).

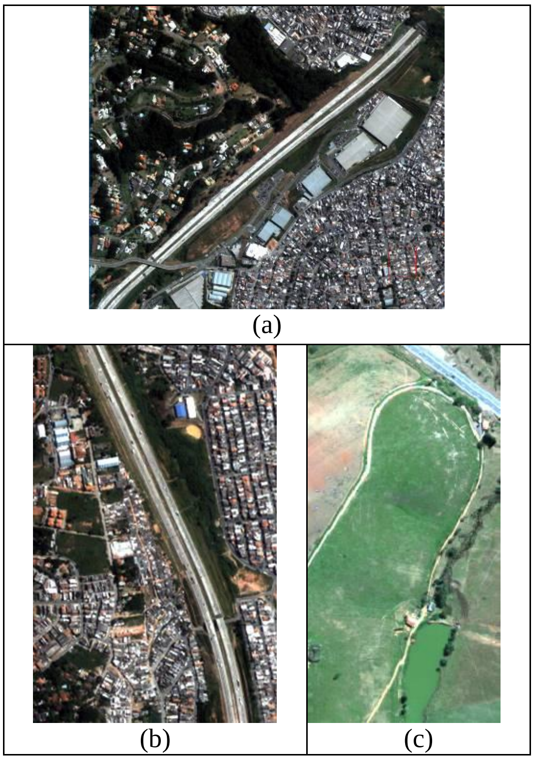
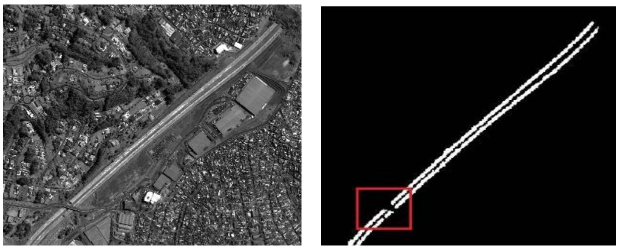


Fig. 1 - Three different levels of difficulty related to the reconstruction of curvilinear features of road networks extracted with flaws: (a) low sinuosity, (b) mean sinuosity, and (c) high sinuosity

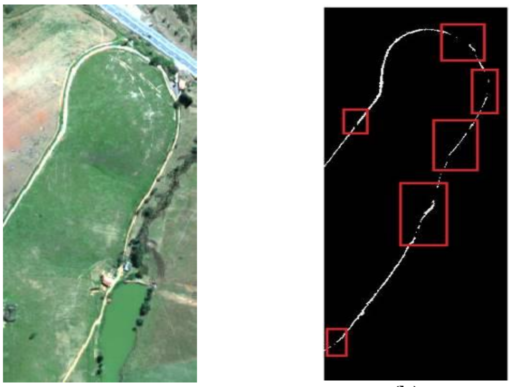


(a) (b)

Fig. 2 - Example of problems with low complexity: (a) original image of curvilinear feature with low sinuosity partially covered by a viaduct; (b) simple single flaw (highlighted by the rectangle) resulting from the process of extraction of road network features.

(a) (b)

Fig. 3 - Example of problems with medium complexity: (a) original image of curvilinear feature with medium sinuosity partially covered by vehicles and with differences in pavement; (b) flaws (highlighted by rectangles) resulting from the process of extraction of road network features.



(a) (b)

Fig. 4 - Example of problems with high complexity: (a) original image of curvilinear feature with high sinuosity, without paving and partially covered by shadows, trees, undergrowth, stains, etc.; (b) flaws (highlighted by rectangles) resulting from the process of extraction of road network features.

The proposed method was applied to all contexts and degrees of difficulty mentioned in this article, each of which was tested separately. The same method was rigorously and systematically applied for all experiments.

The method, presented in the diagram of Figure 5 and proposed in this research, consists in firstly opening the digital image from RS already preprocessed for extraction of road network features. Then visually examine the image containing the road network to find any flaw. Next, for each flaw found, select the image area around the flaws. Finally, apply one or more techniques (active contours, regression and cubic splines) as necessary to reconstruct the flaws and according to the methodology described in following paragraphs.

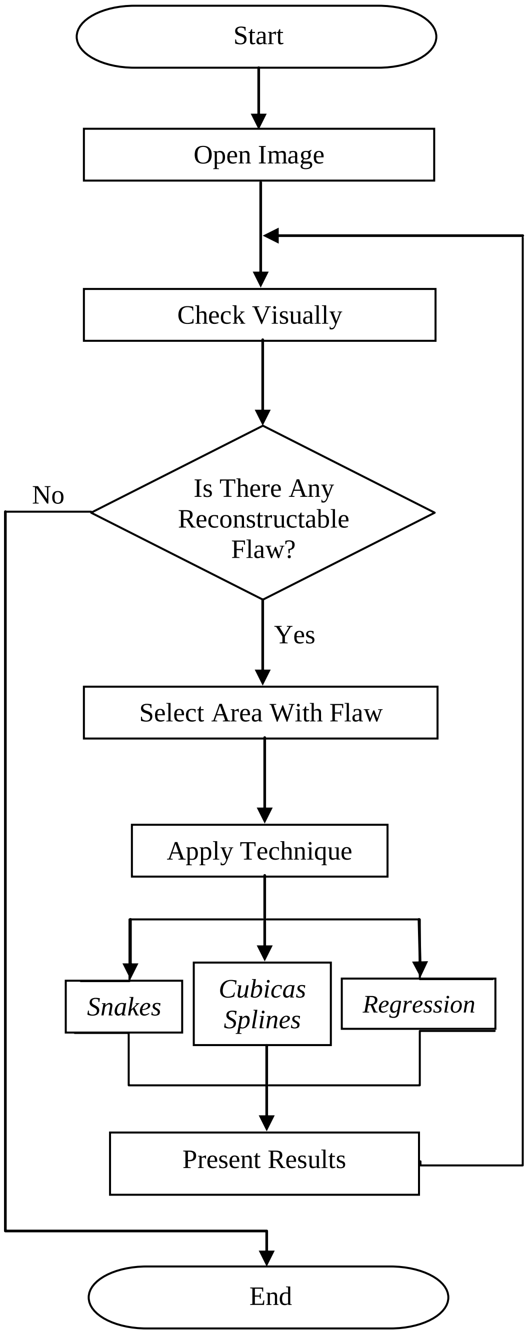


Fig. 5 - Diagram of proposed method.

For the active snake contours, consider all points belonging to the edge of the user selection in the application of the equation of energy minimization until the minimum value is reached or until it completes 400 iterations (this value was determined empirically). The energy to be minimized is called Total Energy as follows:

$$Etotal(v) = Einterna(v) + Eexterna(v). \qquad (1)$$

The first term of Equation (1), *Einterna (v)* is modified at each iteration and the same is given by:

$$Einterna(v) = \frac{1}{2}\int_0^1 w_1(s)\left|\frac{\partial v}{\partial s}\right|^2 + w_2(s)\left|\frac{\partial^2 v}{\partial s^2}\right|^2 ds. \qquad (2)$$

The internal energy is a flexible deformation, since it is adequate to reach the boundary at each iteration, and it is controlled by two positive functions that characterize stiffness and tension, *w1 (s)* and *w2 (s)* at a given point *s* on the curve.
The second term of Equation (1), represents the external energy, as follows:

$$Eexterna(v) = \int_0^1 P(v(s))ds, \qquad (3)$$

where *P (x, y)* is the function that indicates the edge. This function presents values close to '0' when the points in question belong to the neighborhood of the edges of the image, and larger values as the points move away from the edges. Therefore, the total energy is minimized when the snake reaches the edges of the image, and thus there are no more iterations and the total energy is no longer diminished. This is the point at which the application of the active snake contours has been reached to reconstruct the failure in the extraction. If the flaw has not yet been completely rebuilt, another technique must be applied to continue trying to rebuild the same fault.
For regression, apply the method in accordance with the equation given below:

$$M = (Y2 - Y1) \ / \ (X2 - X1). \qquad (4)$$

Equation (4) describes the ordinate and slope of the regression. For Equation (4), *X1*, *X2*, *Y1* and *Y2* are the coordinates of the upper left and lower right corners of the selected area. After applying Equation (4) the application of the regression has been reached to reconstruct the failure in the extraction. If the flaw has not yet been completely rebuilt, another technique must be applied to continue trying to rebuild the same fault.
For cubic splines, apply the curvature function on the set of points that represent the missing area in the image. It is expected that the flaw will be filled. This function determines the cubic polynomials closest to the curve between two given points, which are called breakpoints. Since between two points there are infinite cubic polynomials, some constraints must be applied in order to find a unique polynomial that solves the bad behavior. For the correct application of the method, it is necessary to consider the following restrictions:
1) the first and second derivatives of each cubic polynomial must match on all breakpoints;
2) all internal cubic polynomials must be well defined.
3) the inclination and curvature of the polynomials that approach the curve must be continuous in the breakpoints;
4) the first and last cubic polynomials do not have adjacent polynomials;
5) the first and last breakpoints are adjacent and
6) force the third derivative of the first and second polynomials and the last and penultimate to be equal, respectively.

Given *n* breakpoints, we find *n-1* cubic polynomials with *4* unknown coefficients, so the system of equations will have *4(n-1)* unknowns. However, after applying the constraints described above, the system is reduced to *n* equations and *n* unknowns, easily solved by sparse matrices, which are matrices in which most cells are filled with zero. This is the point at which the application of the cubic splines to reconstruct the failure of the extraction is reached. If the flaw has not yet been completely rebuilt, another technique must be applied to continue trying to rebuild the same flaw.

The application of the techniques active contouring, regression, and cubic splines must be empirical for each of the flaws encountered until all curvilinear features of the road network are reconstructed in an image. Later, repeat all steps for each image to be treated for the reconstruction of curvilinear features of road networks extracted with flaws.

Additionally, the experiments reconstructed curvilinear features of road networks extracted with flaws by applying active snakes contours, in a manner similar to that described in (PETERI et al. 2003); regression, as discussed by (SIRONI et al., 2016); and cubic splines, in accordance with concepts presented by (WU et al., 2009).

Despite the efforts to perform experiments considering different images involving different contexts and levels of difficulty for reconstructing features of road network, the dataset of images used in this research still represents only a subset of all the possible contexts and difficulties that can be found in images from RS. In continuing this research, it is intended to add even more images to the existing image dataset, thus incorporating new contexts and difficulties that will help to continue evaluating the robustness of the method proposed by this research.

III. RESULTS AND DISCUSSION

To evaluate the robustness of the semiautomatic method of post-processing, these methods were applied to a dataset of images containing real images from RS. This set of images provides different contexts and levels of difficulty, so it was possible to perform the experiments for each of the various situations involving the reconstruction of curvilinear features of road networks extracted with flaws found in the whole dataset of image. Each of the experiments was carried out to evaluate if the proposed method is capable of reconstructing curvilinear features of road networks.

To evaluate the proposed method quantitatively and qualitatively, three statistical values were calculated: correction, completeness, and quality (WIEDEMANN et al., 1998). The correction represents the percentage of the number of points that were correctly extracted, as shown in Equation (5):

$$Correctness = \frac{matched\ pixels\ of\ extracted\ image\ comparison}{total\ number\ of\ pixels\ of\ extracted\ image} \quad (5)$$

where *total of extracted pixels* means the total reconstituted pixels for evaluation of the images after reconstitution.

Completeness represents the percentage of points that actually belongs to the area of interest of the image, as shown in Equation (6).

$$Completeness = \frac{matched\ pixels\ of\ reference\ image\ comparison}{total\ number\ of\ pixels\ of\ reference\ image} \quad (6)$$

Quality represents the percentage of accuracy of the extraction and/or reconstitution method, as shown in Equation (7).

$$Quality = \frac{Completeness * Correctness}{Completeness - (Completeness * Correctness) + Correctness} \quad (7)$$

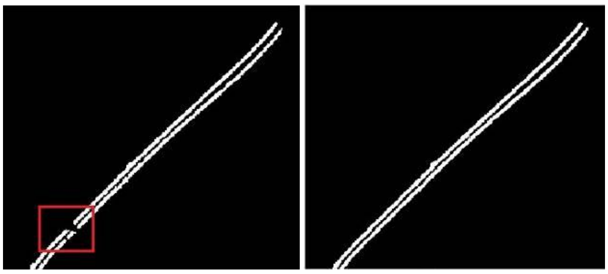
In order to apply the statistical metrics described above and to verify if there was actually an improvement in the image of interest, this research made use of the CARTOMORPH software, proposed and developed by Cardim and Silva (2014). CARTOMORPH has an analysis algorithm that creates a buffer around the area of interest in an image and compares that buffer with another image. During the comparison the algorithm checks the number of points that coincide and differ in the images to be used later in the calculation of the statistical analysis.

CARTOMORPH requires four procedures. First, it is necessary to select three different images: the image of interest (image from the satellite) converted to grayscale; the image with features partially detected in binary; and the ground truth (GT) of the binary image, which represents the ideal result for the area of interest. The second procedure uses the software to calculate the metrics for these images. The third is similar to the first, but one should select the image with the reconstructed features, in binary, in place of the image with partially detected features. The fourth procedure subtracts the results of the second procedure by the results of the first and checks if there is improvement in the quality, completeness, and correction of the images.

Some examples of the application of the proposed method to the dataset of images are shown in Figures 6, 7, and 8. In these figures, letter (a) refers to the original image but converted to gray scale; letter (b) refers to the image obtained by the extraction of road network with features partially detected; and letter (c) refers to the final images after the reconstruction process proposed by this research. The main flaws, present in the curvilinear features before being reconstructed by the application of the method proposed by this research, are highlighted by rectangles in (b).

From a visual analysis of the obtained results, it is possible to notice that the application of the method provided the reconstruction of the main curvilinear features with flaws. This efficiency was also showed by the statistical metrics adopted with the objective of evaluating the detection before and after the reconstruction of the features in each image.

(a)

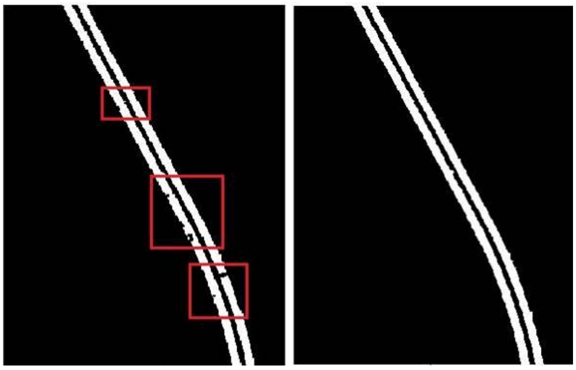


(b) (c)

Fig. 6 - An example of the application of the method in a solution of problems with low complexity: (a) original image converted to gray scale; (b) image obtained by the extraction of road network with features partially detected and flaw highlighted by rectangle; (c) reconstructed image by the proposed method

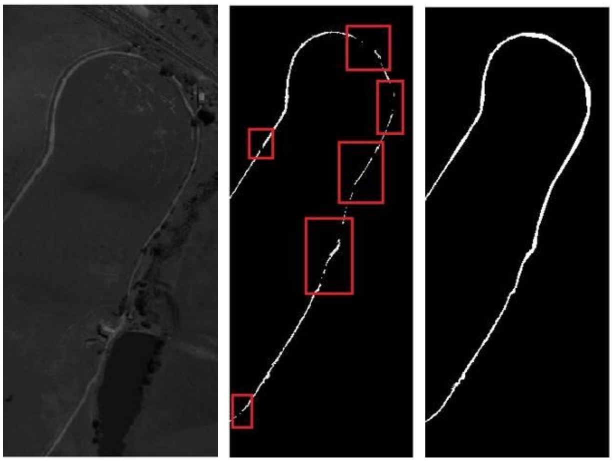
The statistical analysis of the results was entirely based on the method implemented in CARTOMORPH and as described in CARDIM and SILVA, 2014. Thus, the original image was considered as a reference in the manual generation of the GT. With the GT as reference, the values for correction, completeness, and quality were obtained for both the results obtained in the extraction process, containing partially detected features, as well as the results obtained in the feature reconstruction process. The results achieved are presented in Tables 1, 2, and 3, and refer respectively to completeness, correctness, and quality.

(a)



(b) (c)

Fig. 7 - an example of the application of the proposed method in the solution of problems with medium complexity: (a) original image converted to gray scale; (b) image obtained by the extraction of road network with features partially detected and flaws highlighted by rectangles; (c) reconstructed image by the proposed method



(a) (b) (c)

Fig. 8 - an example of the application of the proposed method in the solution of problems with high complexity: (a) original image converted to gray scale; (b) image obtained by the extraction of road network with features partially detected and flaws highlighted by rectangles; (c) reconstructed image by the proposed method

TABLE 1 - INDEX OF COMPLETUDE FOR EXTRACTED AND RECONSTRUCTED IMAGES.

Complexity of the Problem in the Image	Extracted (%)	Reconstructed (%)
Low	95.36	98.42
Medium	87.43	88.36
High	82.25	94.57

TABLE 2 - INDEX OF CORRECTION FOR EXTRACTED AND RECONSTRUCTED IMAGES.

Complexity of the Problem in the Image	Extracted (%)	Reconstructed (%)
Low	94.51	97.98
Medium	84.88	88.09
High	92.74	94.81

TABLE 3 - INDEX OF QUALITY FOR EXTRACTED AND RECONSTRUCTED IMAGES.

Complexity of the Problem in the Image	Extracted (%)	Reconstructed (%)
Low	90.44	96.50
Medium	75.67	78.97
High	77.41	90.04

As can be seen, the image related to the problem with low complexity (Figure 6) presented a flaw in the lower left corner of the image, caused by the overlap of overpass on the highway. The image concerning the problem with medium complexity (Figure 7) was affected by vehicle-caused failures. The image of the problem with high complexity (Figure 8) contained many flaws caused by shadows projected by the vegetation, absence of paving, etc.

From the analysis of the results in Tables 1, 2 and 3, it can be seen that the method proposed in this research reached the objective of reconstructing partially detected features and, therefore, the results of the indices calculated after the reconstruction process were improved on average by approximately 6.4% for completeness, 3.2% for correction and around 9.1% for quality.

This research presents results based on the application of the proposed method for a set of satellite images containing different contexts and levels of difficulty related to the reconstruction of features of road networks. The method proposed by Sironi et al. (2016) was applied to a dataset containing images of road networks with simple topologies, the method proposed by Peteri et al. (2003) was applied to a single image and the method proposed by Wu et al. (2009) was not applied to aerial or satellite images. In addition, the results found by the present research were validated by three different validation metrics, while only one metric, limited to the validation of simple topologies, was used by Sironi et al. (2016) and no validation values were presented for the results found by Peteri et al. (2003). Peteri et al. (2003) suggested the use of more images as well as validation metrics to evaluate results, which shows that this was not done in that study, unlike what was done in the present research. Therefore, the results of this research outperforms those presented by Peteri et al. (2003) and extends the work presented by Sironi et al. (2016) and Wu et al. (2009).It is noted that the results achieved by the present research are quantitative and qualitatively consistent with results found in the scientific literature.

It is also possible to notice that the correctness, completeness, and quality of the reconstruction of curvilinear features of road networks extracted with faults vary according to the context and level of difficulty presented by the feature present in the image. However, when the values presented by the different metrics are compared to each other for the same image, the differences were not significant for all the results found. Future work should investigate whether image filtering applied prior to preprocessing can further reduce these differences.

IV. CONCLUSIONS

The extraction of features of road networks present in digital images from Remote Sensing has attracted the attention of the scientific community for decades, yet this activity is still subject to the occurrence of failures. There is still a need for research on new strategies for reconstruction of features which have only been partially extracted. This article proposes an alternative to improve the results from the extraction of road networks in digital images from remote sensing. The present research developed a semiautomatic method for post-processing digital images from remote sensing in order to reconstruct curvilinear features of road networks extracted with flaws.

The method proposed in this article applied three techniques (active contouring, regression, and cubic splines) to reconstruct features in different experiments. The research presented in this article innovates by proposing the joint and parallel use of these three techniques for the reconstruction of curvilinear features of road network.

The present research is in the state-of-art, since it applied: active contours snakes, in a similar way to that described in Peteri et al. (2003); regression, as discussed by Sironi et al. (2016); and cubic splines in accordance with concepts presented by Wu et al. (2009). However, the work presented by this article outperforms the work presented by Peteri et al. (2003) and expands the works presented by Sironi et al. (2016) and Wu et al. (2009) because it presents results of experiments based on the proposed application for a set of images containing different contexts and levels of difficulty related to the reconstruction of features of road networks.

The results obtained with these experiments show that this research increases the completeness, correctness, and quality of the extraction of curvilinear features of road networks in digital images from remote sensing, even when these images present problems related to different contexts and levels of difficulty for the reconstruction of features. This implies that the method is robust against different adverse conditions captured by the images, including different intensities of sinuosity and different luminosity on given features, the absence of paving, or the presence of shadows, trees, undergrowth, spots, etc.

Although robust, the proposed method still presents results with small differences in levels of completeness, correction, and quality for the extraction of curvilinear features after the reconstruction of the same. The different levels presented by the results are related to the different contexts and levels of difficulty for the reconstruction of features. Future research may investigate whether applying filters to remote sensing images before extracting features may further reduce these differences.

It is hoped that this semiautomatic method for post-processing digital images from remote sensing to reconstruct curvilinear features of road network will continue to stimulate further research on reconstruction of features, within and beyond the Cartography area, as well as allowing the updating of cartographic products with greater completeness, correctness, and quality.

ACKNOWLEDGMENTS

The authors thank the support of the São Paulo Research Foundation (FAPESP) - Processes: 2016/24185-8, 2016 / 09993-0 and 2013 / 25257-4, and the Graduate Program in Cartographic Sciences (PPGCC) – FCT/UNESP.

REFERENCES

[1]. ALEXANDRIA, A. R.; UZUIR, R.; CORTEZ, P. C.; FELIX, J. H. DA SILVA & ABREU, J. S. Método de contornos ativos Snakes aplicado em imagens de ecocardiograma de eixo curto para cálculo de fração de ejeção. **Revista Brasileira de Engenharia Biomédica**, vol.27, n.3, p.147-162, 2011.

[2]. BARSI, A.; HEIPKE, C. & WILLRICH, F. Junction extraction by artificial neural network system jeans. In: **PCV02. Photogrammet. Comput. Vision. ISPRS Commission III**, Graz, Austria, 2002.

[3]. BERTUOL, G. Análise e aplicação da técnica de contornos ativos com métodos de segmentação tradicionais em imagens médicas. **Monografia**. Universidade Federal de Santa Catarina, 2007.

[4]. CARDIM, G. P.; AZEVEDO, S. C.; SILVA, E.A.; MUNHOZ-BRAVO, I. & GARDEL, A. A road network extraction methodology in remote sensing images of low and median spatial resolution. In: **Proceeedings of Pecora 20**, Sioux Falls, USA, 2017.

[5]. CARDIM, G. P. & SILVA, E. A. Development of an algorithm to analyze cartographic features extraction methods in digital Images. In: **Proceedings of ISRSE 35 IOP Conference Series: Earth and Environmental Science**, v. 17, 2014.

[6]. COURTRAI, L. & SÉBASTIEN, L. Morphological path filtering at the region scale for efficient and robust road network extraction from satellite imagery. **Pattern Recognition Letters**, v.83, p. 195–204, 2016.

[7]. GALO, M.; DAL POZ, A. P. & FRANCE, M. F. O uso de feições no controle de qualidade em cartografia. In: **Proceedings of the XX CBC-Cartography Brazilian Congress**. 2001.

[8]. GÉRAUD, T. & MOURET, J. Fast road network extraction in satellite images using mathematical morphology and Markov random fields. **J. Appl. Signal Process**., v. 16, p. 2503–2514, 2004.

[9]. GRÜEN, A. & LI, H. Semi-automatic linear feature extraction by dynamic programming and LSB-snakes. **Photogramertic Engineering and Remote Sensing**, v.63 (8), p. 985e995, 1999.

[10]. JUNIOR SILVA, J. A. C. Análise Comparativa de Técnicas de Contornos Ativos Aplicadas na Segmentação do Ventrículo Esquerdo em Imagens Digitais de Ecocardiograma. **Dissertação de Mestrado**. Engenharia de Teleinformática-Universidade Federal do Ceará, 2010.

[11]. KASS, M.; WITKIN, A. & TERZOPOULOS, D. Snakes: Active Contour Models. **In: 1st International Conference on Computer Vision**, London, England: p. 259-268, 1987.

[12]. MABOUDI, M.; AMINI, J.; HAHN, M. & MEHDI, S. Object-based road extraction from satellite images using ant colony optimization. **International Journal of Remote Sensing**, v. 38:1, p. 179-198, 2017.

[13]. MAYER, H.; HINZ, S.; BACHER, U. & BALTSAVIAS, E. A test of automatic road extraction approaches. **The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences**, v. 36, part. 3, p. 209-214, 2006.

[14]. MENA, J. B. State of the Art on Automatic Road Extraction for GIS Update: A Novel Classification. **Pattern Recognition Letters**, v. 24(16), p. 3037–3058, 2003.

[15]. MESQUITA, V. A. Segmentação Automática do Ventrículo Esquerdo em Imagens de Ecocardiograma Usando Contornos Ativos (*snakes*). **Monografia**. Engenharia de Teleinformática – Universidade Federal do Ceará, 2009.

[16]. OLIVEIRA, R. M. S. de. Extração de rodovias utilizando SNAKES. **Dissertação de Mestrado**. Universidade Estadual Paulista, Faculdade de Ciências e Tecnologia, 2003.
[17]. PETERI R.; CELLE J.; RANCHIN T. Detection and extraction of road networks from high resolution satellite images. **IEEE Proceedings 2003 International Conference on Image Processing.** (Cat. No.03CH37429), 1: I – 301 p., 2003.
[18]. RAVANBAKHSH, M.; HEIPKE, C. & PAKZAD, K. Road Junction Extraction from High-Resolution Aerial Imagery. **The Photogrammetric Record**, v.23 (124), p.405–423, 2008.
[19]. SIRONI, A.; TÜRETKEN, E.; LEPETIT, V.; FUA, P. Multiscale Centerline Detection. **IEEE Transactions on Pattern Analysis and Machine Intelligence**, v. 38: 7, 1327 - 1341 p., 2016.
[20]. SOILÁN, M.; TRUONG-HONG, L.; RIVEIRO, B. & LAEFER, D. Automatic extraction of road features in urban environments using dense ALS data**. Int J Appl Earth Obs Geoinformation**, v. 64, p. 226–236, 2018.
[21]. UNSALAN, C. & SIRMACEK, B. Road network detection using probabilistic and graph theoretical methods. **IEEE Trans. Geosci. Remote Sens**., v. 50(11) p.4441–4453, 2012.
[22]. WANG, W.; YANG, N.; ZHANG, Y.; WANG, F.; CAO, T. & EKLUND, P. A Review of Road Extraction
[23]. from Remote Sensing Images. **Journal of Traffic and Transportation Engineering**, v. 3(3), p. 271–282, 2016.
[24]. WIEDEMANN, C.; HEIPKE, C.; MAYER, H. & JAMET, O. Empirical Evaluation of Automatically Extracted Road Axes. In: **Proceedings of the IEEE Computer Society Workshop on Empirical Evaluation Techniques in Computer Vision**, p. 172–187, 1998.
[25]. WU B-F.; LIN C-T; CHEN Y-L. Dynamic Calibration and Occlusion Handling Algorithms for Lane Tracking. **IEEE Transactions on Industrial Electronics**, Volume: 56, Issue: 5, Pages: 1757 - 1773, 2009.

Raíssa Souza,etal. " Semiautomatic Method for Reconstruction of Road Network Detected From Satellites Image." *IOSR Journal of Engineering (IOSRJEN)*, 10(4), 2020, pp. 32-43.