# A ROAD NETWORK EXTRACTION METHODOLOGY APPLIED IN REMOTE SENSING IMAGES OF LOW AND MEDIAN SPATIAL RESOLUTION

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## ABSTRACT

Nowadays, there is a great demand of remote sensing images that must be processed to obtain the desired characteristics. This fact is driven by the constant increase of Geographic Information Systems (GIS) importance and the needs of acquisition and update of spatial data. Furthermore, it essential that the spatial data are updated and accurate. In this sense, the roads networks became a very interesting cartographic feature, since it suffer updating constantly and needs an efficient and fast way to update it. There are several researches in literature containing road extraction as the main objective, which use different sets of digital image processing techniques, such as mathematical morphology, classification and growing region methods. However, there is still no agreement on the best methodology to perform this activity. It is very common to find researches applying a methodology that works in a specifically scene and with images acquired by a specific sensor. This fact restricts the methodologies developed and makes new methodologies arise frequently. This paper presents an in progress work aiming to develop a methodology to detect a road network from remote sensing images. The methodology proposed is based on the mathematical morphological theory, which has as advantage the fact to analysis the shape and structure of the objects in the image. The main idea is to perform a preprocessing step, using some mathematical morphology operators, trying to highlight the targets that have linear structures. Thus, the segmentation can be performed. Remote sensing images of low and median spatial resolution were used and the methodology was capable to detect the majority of roads presents in the scene. The experiments performed presents promising results when evaluated statistically by some literature metrics. Furthermore, we intend to apply the methodology in high resolution images to verify the results.

KEYWORDS: Road extraction methodology; road network; mathematical morphology.

## **INTRODUCTION**

The remote sensing data have been widely used for cartographic studies. Remote sensing is the name given to the cartographic studies using data that are collected without a physical contact with the object measured. Sensors, placed in airplanes or satellites for example, are able to acquire the remote sensing data. The most common remote sensing data, used in cartographic research, is the digital image. The remote sensing images can be used for several purposes, such as urban cadastral studies and road maps updating. Considering the need to have updated road mapping, it is possible to find in the literature several researches aiming to automatic extract road networks from remote sensing images.

There are several theoretical concepts used by authors to develop and propose new extraction methodologies, such as beamlet transformation (Sghaier and Lepage, 2016), convolutional neural networks (Li et al. 2016; and Zhong et al. 2017), partial differential equations (Leonardi et al. 2013) and mathematical morphology (Ma et al. 2013; Wang and Shan 2012; Courtrai and Lefèvre 2016; Valero et al 2010; Cardim et al. 2014a). Among them, mathematical morphology theory is widely used due to its ability to maintain the geometry structure of the interest target after a processing step (Soille 2003).

Despite the high number of methodologies proposed for road network extraction, there is no ideal solution for all

situations. Furthermore, the recent great availability of high-resolution remote sensing images has made studies of road extraction methodologies using low-resolution remote sensing images, for large areas, become scarce. In this sense, this paper proposes a novel method for road network extraction from low-resolution remote sensing images. The proposed method is based on mathematical morphology, automatic Otsu segmentation and a geometric step analyzing the target structure. Statistical metrics, defined in the literature (Wiedemann et al. 1998; Wiedemann 2003; Cardim et al. 2014b), were calculated to evaluate the results and confirm the method's ability to extract road networks.

The rest of the paper is organized as follows. Section 2 presents the study area describing the image dataset used in the paper. Section 3 summarizes the road extraction methodology proposed. Section 4 presents the results obtained with the proposed methodology. Section 5 presents a brief conclusion about the results obtained with the proposed methodology.

## STUDY AREA AND DATASET DESCRIPTION

To verify and evaluate the methodology presented in this paper, we obtained the panchromatic layer of a remote sensing image, acquired in July 2017, by CBERS satellite, which has spatial resolution of 5m per pixel. The images are from Alta Paulista region, a region of the São Paulo state in Brazil, containing the principal interest point the Presidente Prudente city, as presented by Figure 1. This area was chosen due to the recent renovation and extensions carried out by the governments on the roads in this area. Considering the highways as the study focus, the remote sensing image was split in six subsamples, which contain highways as interest features. Figure 2 shows two subsamples selected to be presented in this paper. (Figure 2).



Figure 1. Selected image for the study.



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### Figure 2. Subsamples used as examples. METHODOLOGY

The methodology proposed in this paper is based on digital image processing with focus on the mathematical morphology theory. The methodology is organized in four stages: preprocessing, segmentation, post-processing and a skeletonization; which are described below. Figure 3 presents the road extraction methodology proposed in the paper.



#### **Preprocessing Stage**

In the first stage, we perform a morphological opening function, using a disk with eight pixels of radius. It removes the interest roads from the original image making necessary its recovery. In this way, we recover the interest feature subtracting the opening result from the original image. It enhance the roads of the image as the interest feature. The steps described before compose the pre-processing stage, which results in a gray tone image highlighting the interest road.

#### **Segmentation Stage**

Continuing the methodology, the Otsu method is performed composing the segmentation stage. The Otsu was chosen by the capability of automatic segment a gray image, transforming it in a binary one. It uses statistical calculations to determine automatically a threshold that create two classes with the highest interclass variance possible.

#### **Post-processing Stage**

The third methodology stage aims to reduce noises and improve the segmentation results. The first step, of the third stage, is to apply the morphological closing operator to group targets separated during the segmentation. With the targets grouped, the salt and pepper noises are removed applying, respectively, the morphological area open and area closing functions.

The steps described before are based on the spectral features of the road in the studied image. In this way, some nonroads features are also segmented generating some errors in the detection process. To improve the previous results the methodology contain a step based on the road geometry. Considering that roads are elongated structures, we calculate the area (S) and perimeter (C) of each target in the image to obtain a ratio (t) of the area square root to the perimeter, as described in the Equation 1 (Ma et al. 2013).

$$t = \frac{\sqrt{S}}{C} \tag{1}$$

The Equation (1) allows the methodology to differentiate some roads and non-roads targets. All the ratios values are ordered and only the targets with the lowest t values are kept as the interest road. This step makes the methodology identify only the targets with elongated geometry. After the last step described, the methodology achieve the extraction of the entire interest road, however it still not being the road main axis.

#### **Skeletonization Stage**

Since the images used in the paper is of low spatial resolution, the methodology should acquire the main axis of the **Pecora 20 -** Observing a Changing Earth; Science for Decisions—Monitoring, Assessment, and Projection November 13-16, 2017 **•** Sioux Falls, SD road detected. In this way, the morphological thinning algorithm is performed to detect the skeleton of the interest road. However, the thinning algorithm creates a high number of small segments as noises, which are also known as spur segments. To remove it, the last methodology step consists in perform the morphological spur filter, which results in the extraction of the main axis of the interest road.

## **RESULTS AND DISCUSSION**

To exemplify the methodology proposed, this section presents the results obtained in each step of the methodology for the example images in Figure 2. The example images used in this paper has a highway as interest feature, which must be detected after the application of the methodology.

As mentioned before, the first methodology step is based on exclusion of the interest road, by the application of a morphological opening operator. However, the interest road is recovered using a simple subtraction of the opening result in the input image, which highlight the interest feature. Figure 4 shows the result of this first methodology stage applied in the example images.



Figure 4. Difference between input and opening image.

The second methodology stage is the segmentation, which is automatically achieved using the Otsu method. Figure 5 shows the result of the segmentation step.



Figure 5. Segmentation by Otsu algorithm.

Once segmented, the image has to be post-processed to improve the extraction result. The first post-processing step is the application of morphological closing operator aiming to connect some targets that was separated during the

segmentation step. The morphological closing operator was applied using a structure element of disk shape with two pixels of radius to connect closest targets. However, the images still containing salt and pepper noises, which are reduced after the respective application of the morphological area open and area closing operators. The area open algorithm was applied with a threshold of 1000 pixels while for the area closing was used 500 pixels of threshold. The thresholds were empirically defined according to spatial resolution and image dimensions. Figure 6 shows the example images after the noises reduction.



Figure 6. First post-processing results.

As mentioned in the methodology section, all the steps before are based on image and road spectral characteristics. In this way, some non-roads features, with similar spectral characteristics, are also detected producing errors in the extraction process. To improve the results, a geometry analysis of the targets detected before is performed. Considering that roads have elongated structure, the methodology calculates the area and perimeter of each target verifying which of them can be considered as the interest road. A ratio between the area square root and perimeter is calculated for each target in the image and only targets with the smallest ratio values are maintained as interest roads. Figure 7 presents the result obtained after the geometric analysis step.



Figure 6. Results after a geometric analysis step.

As mentioned in the methodology description, the last stage is based on the acquisition of the road main axis. It is achieved performing the morphological thinning algorithm and, after, the spur morphological filter to remove the spur noises. This stage results in the final extraction of the road main axis. Figure 7 presents the result of the road main axis extraction.



Figure 7. Road main axis extraction results.

The last step produces the result image of the proposed methodology. However, the result has to be evaluated in some way. The simplest evaluation verified in the literature consists in overlap the result image in the input one to make possible a visual comparison and analysis of the detected road position. Figure 8 presents the extraction result over the input image, where the blue color pixels represents the extraction results.



Figure 8. Extraction result over the input image.

However, the visual analysis is directly related to the visual ability of the user and, therefore, should not be used as a quality reference. In this way, a mathematical analysis must be performed to evaluate the road extraction methodologies. Wiedemann (Wiedemann, 2003) defined the most widespread method for mathematical evaluation of road extraction methodologies. The author describes some statistical metrics that are commonly used in the literature to evaluate new road extraction methodologies. Furthermore, it is possible to find in the literature an adaption, of the methodology cited before (Wiedemann, 2003), that calculates the metrics for road extraction in high-resolution images (Cardim et al., 2014b). To evaluate the extraction results, it is necessary a reference image, also known as ground truth, which is considered as an ideal result. The extraction methodology is evaluated by comparing the automatically extracted road main axis with the reference image. The comparison is performed pixel-by-pixel using an acceptance buffer (tolerance), which is disposed separately on both images. To consider the pixel as a coincident one, it has to be in the acceptance buffer of the other data during the comparison. Figure 8 presents how this comparison is performed.



Figure 9 (a) presents the comparison of the extracted image, where the false positive errors, obtained by the extraction methodology, are verified. On the other hand, Figure 9 (b) presents the comparison of the reference image, where the false negative errors are calculated. With the amount of false positives and false negatives errors verified, it is possible to define the completeness and correctness metrics, Equations 2 and 3 respectively.

$$completeness = \frac{matched \ pixels \ of \ reference \ image \ comparison}{total \ of \ pixels \ of \ the \ reference \ image}$$
(2)

$$correctness = \frac{matched \ pixels \ of \ extracted \ image \ comparison}{total \ of \ pixels \ of \ the \ extracted \ image}$$
(3)

The completeness metric describes the percentage of the reference image that was corrected extracted by the methodology proposed while the correctness metric describes the percentage of the extracted image that correspond to the reference image. For both metrics, the optimal value is 1. The completeness and correctness metrics are the two most important metrics described by Wiedemann (2003) and, therefore, they were used to statistically evaluate the extraction methodology proposed in this paper. Table 1 presents the results obtained specifically for the two images presented in this paper and an average value calculated for all test images used.

Table 1. Statistical analysis.		
Dataset	Completeness	Correctness
Image (a)	0.9092	0.5171
Image (b)	0.9440	0.5261
Average	0.8233	0.4883

Visually the main axis road extracted is properly positioned in the center of the interest roads. However, it still having some detected segments that do not correspond to the interest road. In this way, the statistical analysis was performed calculating the completeness and correctness metrics. The completeness values demonstrate that, in general, the road are extracted almost by complete using the methodology proposed. On the other hand, the correctness obtained low values indicating a high presence of false positive errors. In other words, the proposed methodology was able to detect the interest road from the CBERS images, although, even after all the post-processing steps, the methodology continues detecting others features as the interest roads.

### CONCLUSION

Intending to obtain the road main axis from low spatial resolution remote sensing images, a road extraction methodology was developed. The proposed methodology was applied in panchromatic layers of images acquired by CBERS satellite. The method developed is based on mathematical morphology theory aiming to perform the extraction

maintaining the geometric structure of the targets.

Considering the importance of road mapping for urban planning, a novel extraction methodology was proposed. The interest roads extracted are visually properly located in the road's course indicating the correct detection of the road centerline. However, it is possible to perceive the existence of segments of lines detected that do not correspond to the interest road producing errors of false positive type. In this way, the results obtained were statistically evaluated to verify and quantity mathematically the errors generated during the extraction process. As in visual analysis, the statistical evaluation confirms that the extraction methodology achieved the goal of detect the road main axis with completeness values over 90%. Nevertheless, the statistical analysis also proved the existence of a high number of segments not corresponding to the interest road achieving correctness values around 50%.

Despite the low number of false negatives errors, the methodology proposed has to be improved in the pre and postprocessing to achieve a lower number of false positive errors and, consequently, better correctness values. In this way, for future works, we intend to improve the post-processing including some others steps based on the targets geometry aiming to differentiate the detected segments that still not corresponding to the interest road. Furthermore, a bigger dataset has being planned to verify the efficiency of the proposed methodology using others images characteristics.

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