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Use of genetic algorithms as detectors of centerlines of local roads on digital images

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Resumo - USO DE ALGORITMOS GENÉTICOS COMO DETECTORES DE EIXOS DE ESTRADAS VICINAIS EM IMAGENS DIGITAIS. Nesse trabalho, é proposto o uso dos algoritmos genéticos no processo de detecção de linhas retas, ou segmentos, que caracterizam o eixo de estradas vicinais. O processo de detecção de segmentos é realizado de forma iterativa, em imagens digitais, onde dois segmentos candidatos ao eixo de estradas são detectados em cada passo (iteração). A validação dos resultados, obtidos pelo método proposto, foi realizada com base em uma imagem de referência, vetorizada manualmente. O índice de acurácia foi computado como a porcentagem de pixels detectados erroneamente. Embora o número de experimentos seja modesto, os resultados mostram que o método proposto é promissor.
Palavras-chave: estradas vicinais, algoritmos genéticos, detecção de segmentos.

Abstract - In this work, the use of genetic algorithms is proposed as detectors of straight line segments that characterize a rural road. The segment detection process consists of iterative procedures on digital images, where each step results in two possible segments for the centerlines. The validation of the results produced by the proposed algorithms was based on a manually vectorized reference image. The accuracy index was computed as the percentage of wrongly detected pixels. Despite the modest number of experiments, the results have shown the proposed method to be promising.
Keywords: rural road, genetic algorithms, detection of straight segments.

1. Introduction

Since the 1970s, multispectral remote sensing has been a useful tool for obtaining spatial information. Remote sensing images provide data for different purposes, such as cartography, geology or forestry (Richards & Jia, 1987; Swain & Davis, 1978). Technological advances, such as increase of spatial resolution, enable more detailed studies about the earth's surface to be done. In less than three decades, the spatial resolution has moved from many meters to centimeters. This new scenario demands also new techniques in image processing.

Several studies, using high spatial resolution data, have been done by professionals from several areas (Liu *et al.*, 2003). They point out that the exploration of context has a large significance, nowadays, with the increase of the spatial resolution.

The effect of contextual information on the classification process and feature extraction is a typical example of an emerging challenge. The accuracy in those processes can increase if a contextual analysis is done. Features like constructions, courts and roads are difficult to be extracted on digital images, mainly due to the large spectral confusion.

This paper focuses on the development of a tool for road extraction. There are two different processes in the extraction of roads: the automatic and the semi-automatic one. There is no participation of the analist in the first, while the second requires the analyst to provide information, a priori, to the program (Wang *et al.*, 2005; Perez-Jimenez & Perez-Cortes, 2006). The automatic or semi-automatic extraction of roads, either rural or not, reduces the tedious work of digitizing or vectorizing, and also reduces costs (Liu *et al.*, 2003). This practice is common in departments that use road maps, like mapping and road agencies.

A useful approach on the extraction of roads is modeling the road net. For this purpose, the intrinsic model is used. This model is called intrinsic because it is related to the characteristics of the analyzed feature which define a road, such as: length, width, spectral information and linearity. The intrinsic model includes three intermediary models: the geometric one, which takes into consideration road geometric information; the radiometric, which is related to the grey levels on the image; and, finally, the topologic, related to the road arcs and nodes. This paper is concerned with the first two models.

Several studies have been done on the topic of road detection (Baumgartner *et al.*, 1999; Wiedemann & Hinz, 1999; Eker & Seker, 2004; Hasegawa, 2004; Hu & Tao, 2007). Some of them try to extract roads by using algorithms which improve the detection of the geometric attributes of this feature (Mayer & Steger, 1998; Bacher & Mayer, 2004). Optimal algorithms however, demand a high computational cost. Other approaches, that use sub-optimal methods, have been used on the attempt at reducing computational costs (Mirmehdi *et al.,* 1997; Valadan Zoej & Mokhtarzade, 2004). Genetic algorithms are examples of the second group of algorithms (Wang Fan, 1996). In this context, we propose to implement a method to extract linear segments which characterizes rural roads on high resolution satellite images, using the advantages of the genetic algorithms.

2. Fundamental concepts

2.1. Genetic Algorithms

Goldberg (1989), one of the precursors of genetic algorithms (GA's), described them as being a method of optimization, which consists of a search based on the principles that rule natural selection and genetic evolution.

The process can be summarized as follows. An arbitrary set of solutions for the problem is chosen in order to form an initial population. Each solution is coded in a binary chain, resembling a genetic chain. This set of chains, i. e., the population, is submitted to an evolutionary process, in which the least favorable solutions are discarded and the best suited are preserved and matched in order to create new improved solutions (individuals). The new solutions, together with the best solutions of the original set, are used to build a new population. This process is repeated until an optimal solution is achieved, i. e., when the solution of the problem is found.

The basic scheme of the genetic algorithms is composed by the following components: codification of the variables (chromosome) and configuration of the initial population; determination of the fitness function of each individual; selection process and genetic operators (crossover and mutation) which manage the reproduction process (Goldberg, 1989; Mitchell, 1997; Michalewicz, 1999).

2.2. Selection technique

According to Goldberg (1989), the evolutionary algorithm is based on the simple Genetic Algorithms, and its selection technique, is known as elitism. Selection by elitism is simple and has low computational cost. It can be processed as follows: a) sorting the individuals, on descending order, according their value of fitness; b) discarding the individuals with lowest fitness value (about 25% of the population); c) a set, composed by the best individuals, the elite, is used to compose the new population. The size of the group (*Tpop*) can vary around 25% of the population; d) the remaining individuals are then used to breed a new generation.

2.3. Genetic operators

The next generation, the improved population of solutions, is the result of two genetic operators: crossover (recombination), and/or mutation. The genetic operators have the function of stimulating the evolution of the specie.

In crossover, two or more parents exchange genetic material between them, creating their children. The new solution shares some of the characteristics of its parents. The crossover operator is based on the random choice of a single point (point located between any two loci) in each one of the two parents and, subsequently, the exchange of genes is executed between those two parents, as shown on figure 1A.

The mutation alters the genetic code randomly, i. e., one or more genes, randomly chosen, are modified in one individual. The result of the mutation is a mutant child. The objective of the mutation is to introduce new genetic material and to simulate evolution. The selection of the chromosomes for the application of those operators is done randomly. Figure 1B shows an example of mutation, where the fourth element of a binary chain is inverted.

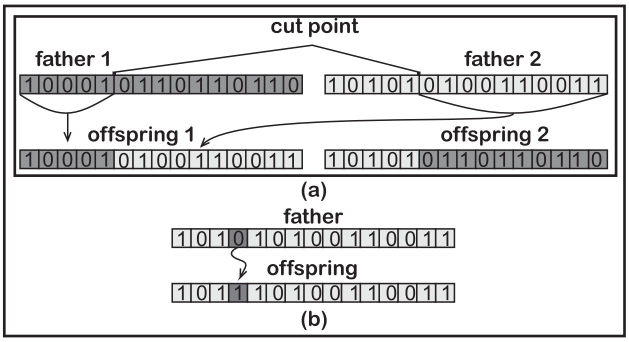

Figure 1. Crossover (A) and (B) mutation operators.

3. Methods

The extraction of linear features, such as rivers and roads, is widely used in areas like photogrammetry and remote sensing (Jeon *et al.*, 2002). This process is based on the merge of spatial and spectral characteristics of the object of interest. It is known, however, that a feature is hardly described by only one attribute. Therefore, the similarity between two features can be computed as the combination of more than two attributes. For the case of rural roads, which are the feature of interest on this paper, we make use geometric and spectral attributes.

In the proposed road model, a road is described as a collection of contiguous segments which define the axis of the road. The proposed method is semi-automated, that is, two points which belong to the road are provided in order to start the search process. These points define an initial orientation.

The method can be described as follows. First, the user (or analyst) provides a segment which belongs to the road, called segment of reference. This segment is represented by two pairs of coordinates of the end points, in other words, it is defined by two pixels. The first segment is also used as a spectral reference, for the computation of spectral similarity with other selected segments. The first segment, therefore, should be spectrally representative of the road.

A simple example of a road is shown in figure 2B to illustrate the process. The road is displayed as a white area, while the background appears grey. Considering having the initial segments (in figure 2B), the aim is to obtain other segments which are consecutive (BC and CD) and belong to the same road. In order to find the next two segments, two sets of likely points are defined in the neighborhood of the first segment, as shown in figure 2B. The first one (C) lies in the neighborhood N1 (Fig. 2A), around point B (reference); the second (D) lies a little farther, in a second neighborhood N2 (Fig. 2A) of B.

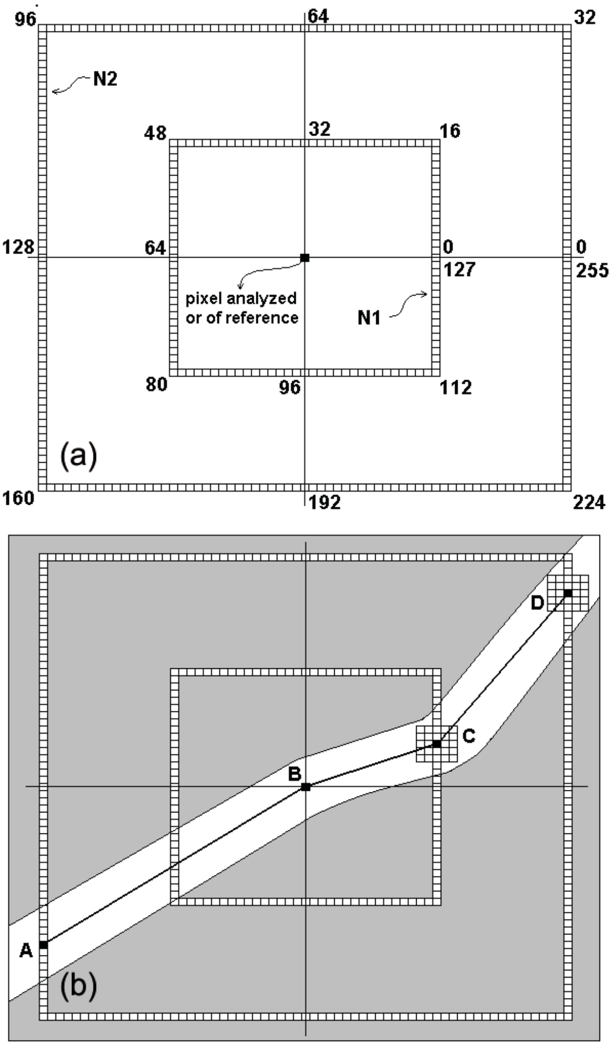

Figure 2. Space of search N1 and N2 (A), and (B) Simple example of road.

Since there are several segments that fulfill these constraints (space of search), the genetic algorithms are used to find the segments which best represent a road. After the first iteration, the two most likely segments are found and, automatically, the algorithm goes to the second iteration. In this iteration, the new segment of reference is defined by the extreme coordinates of the two segments found in the previous iteration (the first pair of coordinates of the first segment and the second pair of the second segment). That process is repeated until the entire road is detected.

3.1. Codification

Since the position of the next likely nodes can be described by an integer, according to their position in the selected neighborhood (Fig. 3), a binary chain is used to encode a solution. The solution can thus be described by two integers. The first is a seven bits integer related to the position of the end of the second segment (BC). The second, an eight bits integer, describes the position of final edge of the third segment (CD). Therefore, the binary chain of each individual has 15 binary elements (genes). Two hypothetical individuals are illustrated on figure 3. In the first chain, the numbers 6 (0000110) (point C in Fig. 2B) and 27 (00011011) (point D in Fig. 2B) are stored. The second chain (Individual 2) contains two random numbers 76 (1001100) and 12 (00001100).

After coding, the initial population is created randomly as a group of *n* individuals. The size of the initial population is defined by the analyst. The next populations of the evolutionary process are created iteratively, without the participation of the analyst.

3.2. Proposal of the fitness function

The search for the best segments, performed by the genetic algorithms, is guided by a genetic fitness function. This function is particular for each problem and describes the suitability of each individual to the solution of the problem. In our case, the fitness function is composed by three parameters. The first parameter defines the co-linearity between two line segments. That is, for short distances, it is supposed that two segments are aligned.The second parameter represents direction changes of contiguous segments. Finally, the third parameter does not involve geometric information, but only spectral similarity. It indicates how similar the grey level of the new segments is, in comparison to a reference value, which is obtained from the seed segment.

Individual 01	0 0 0 0 1 1 0 0 0 0 1 1 0 1 1	= 06 e 27
Individual 02	1 0 0 1 1 0 0 0 0 0 0 1 1 0 0	= 76 e 12

Figure 3. Hypothetical examples of binary chains or chromosomes.

In this paper, this function includes characteristics of the potential segments that compose the road, represented by three factors: a) co-linearity factor; b) direction change factor; and c) spectral similarity factor.

The fitness function is the combination of these three factors, as shown in equation 1. The relevance of each factor is implemented by weighing them:

$$fitness = [(a*p\_L) + (b*p\_D) + (c*p\_S)] \qquad (1)$$

where *ba*, and *c* are the weights given to each factor and are estimated experimentally.

3.2.1. Co-linearity factor

The co-linearity of two segments (*p_L*) is computed comparing the distance between the extremes of two segments and the sum of the length of both segments, according to equation 2, as shown on figure 4.

$$p\_L = \frac{distance\ 3}{distance\ 1 + distance\ 2} \qquad (2)$$

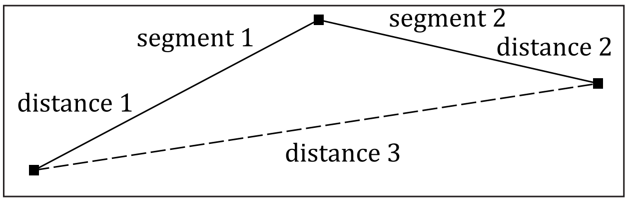

Figure 4. Definition of the co-linearity parameter.

3.2.2. Change of direction

The direction of the new segment, in relation to the previous one, is computed based on the angle between the two segments. The angle between the directional vectors of the segments is computed by equation 3.

$$\cos(\alpha) = \frac{\bar{X}\cdot\bar{Y}}{\|\bar{X}\|\ \|\bar{Y}\|} \Rightarrow \alpha = a\cos\left(\frac{\sum_{i=1}^{m} x_i y_i}{\|\bar{X}\|\ \|\bar{Y}\|}\right) \qquad (3)$$

where m is the space dimension. $\bar{X}$ e $\bar{Y}$ are the directional vectors to the two segments, as shown in figure 5. The angle (α) between the segments is constrained to be larger than ninety five degrees (that is *d < -0,087* equation 4), in order to avoid the return of the road.

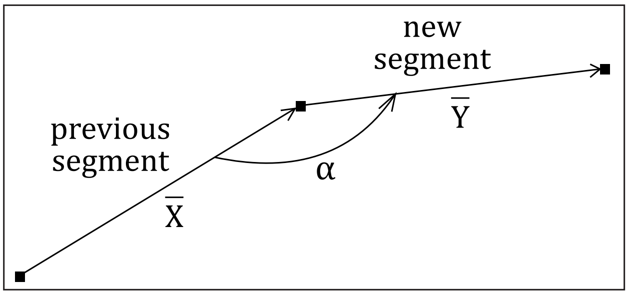

Figure 5. Angle between two vectors.

Then, the factor (p_D) related to the relative direction of the new segment is computed according to equation 4:

$$p\_D = \begin{cases} |d| \quad se \quad d \le -0.087 \\ 0 \quad se \quad d \ge -0.087 \end{cases} \tag{4}$$

where $d = \cos(\alpha) = \dfrac{\overline{X} \cdot \overline{Y}}{\|\overline{X}\| \; \|\overline{Y}\|}$

3.2.3. Spectral similarity

The measure of spectral similarity represents, quantitatively, the similarity between two sets of pixels in terms of gray levels. For reasons of mathematical simplicity and low computational cost, the Euclidian distance (*DistE*) is used in this paper. When the seed segment is given by the user, a reference sample is extracted from the region around the first segment. The mean gray level value of this sample is chosen as the reference value and will be used to evaluate the similarity between the following segments. The Euclidian distance between two samples (x, y), for a m-dimensional space, can be computed as follows:

$$DistE(X,Y) = \sqrt{\sum_{i=1}^{m} (x_i - y_i)^2} \tag{5}$$

Like the other factors, the value of the spectral factor is scaled to between 0 and 1. That is achieved dividing the Euclidian distance by the largest one in the image (equation 6).

$$\text{Const2} = \text{Max}(\text{ DistE(X,MIN)}, \text{DistE(MAX,X)}) \tag{6}$$

where X is the mean digital value of the reference sample; MIN and MAX are the minimum and maximum digital value of the image, and *DistE(X,Y)* is the Euclidian distance between X and Y.

Finally, the spectral similarity factor (p_S) is established according to equation 7.

$$p\_S = \begin{cases} 1 - \left(\dfrac{\sum_{i=1}^{m} DistE(i)}{const2} \right) & if \quad \max(DistE(i)) \le const1 \\ \dfrac{1}{\sum_{i=1}^{m} DistE(i)} & if \quad \max(DistE(i)) > const1 \end{cases} \tag{7}$$

where *m* is the total of distances. For this paper *m = 2* . max(*Dist*(*i*)) is the value of the maximum distance calculated in each iteration.

The experiments have shown that, for an 8-bit image, the value of the first constant (const1) must be less than 115. It is important to emphasize that these values were analyzed only for the road feature.

3.3. Genetic parameters and weights

The weights (*a, b* and *c*) involved in the fitness function were fixed after a series of experiments. The set of weights that presented the best results was: *a* = 0.2, *b* = 0.2 and *c* = 0.6. Other experiments, which lie outside the scope of this paper, were done in order to search for other possible combinations. Some experiments showed good results, but only in specific cases. For straight lines, for example, increasing the weights for *a* and *b* provided better result. However, on curves, some errors occur if the same configuration is used.

The experiments suggest the following configuration for the genetic algorithms: a population with 80 individuals; mutation probability equals to 0.01; crossover probability equals to 0.7; and the maximum number of iterations equals to 300. The size of the elite was of 20 individuals.

3.4. Validation of the results

The validation process is based on visual analysis. For that purpose, the roads were manually digitized on the screen. The result is later used in order to evaluate the success of the proposed approach. Figure 6 shows an example of the result of the visual analysis: (Fig. 6A) original image, (Fig. 6B) digitized road (Fig. 6C) digitized road overlaid to the original image.

The validation is performed based on the comparison between the vectorized image and the resulting image of the proposed methodology. The error is defined as the percentage of pixels, obtained through the semi-automatic approach, that lie outside the road on the reference image.

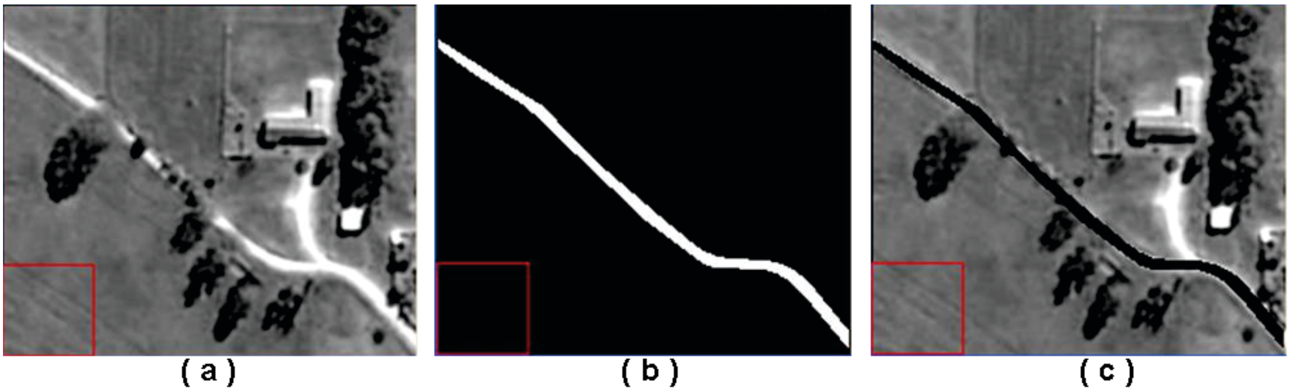

Figure 6. Vectorization of road: (a) Original image, (b) Digitized road, and (c) Digitized road overlaid on the original image.

4. Results and discussion

It is worth to emphasize that the images used in the experiments were obtained from the Google Earth. Thus, the spectral bands are not the original ones. Only one band was used in the tests. Analyzing the grey level variation of each spectral band, it was concluded that the image of the visible-red spectral region of the electromagnetic spectrum can better define the roads, because it enhances the spectral difference between bare soil and vegetation. Therefore, as these two features predominate on the images, only the red band was used.

In the following items, different sub-images are shown to illustrate the experiments. Each experiment presents a particular challenge, due to the nature of the scene.

4.1. Extraction of a road with sinuous curves

A sinuous road was analyzed in this experiment. The road network in the scene has curves and junctions, as shown in figure 7. The detected road is overlaid to the original image (Fig. 7). In spite of some errors, the performance of the genetic algorithms can be considered good, because it followed the road, even when some errors occur during the iterative process. Only one very sinuous curve was not detected very accurately. The bifurcations were ignored. That error occurred due to the maximum size allowed for each segment. The reduction of that size brings a minimization of the error and, consequently, the curve could be much better defined. On the upper right side on figure 7, another type of error is noticed. This error can be explained by the fact that the algorithm selects candidate segments randomly, resulting in sub-optimal solutions. The error is caused also by the influence of the co-linearity and direction parameters. Increasing the number of iterations would be a solution for that problem, but can lead to larger processing time.

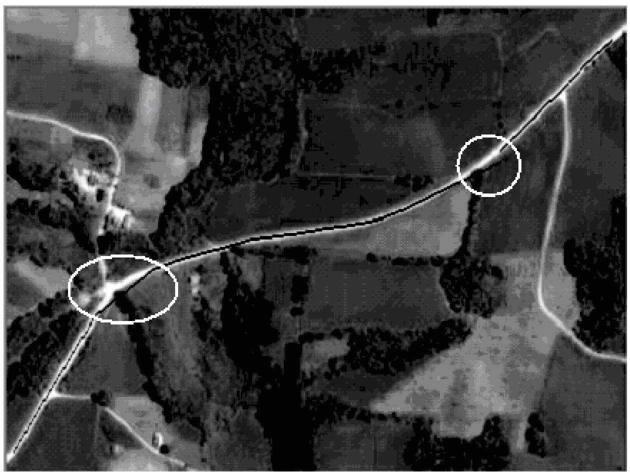

Figure 7. Trace of the detected segments (first experiment).

After comparing the result with the reference image (Fig. 8), obtained by visual analysis, it was observed that from the total of 789 pixels, 673 were correctly detected. Therefore, the error according to the evaluation method was 14.7%.

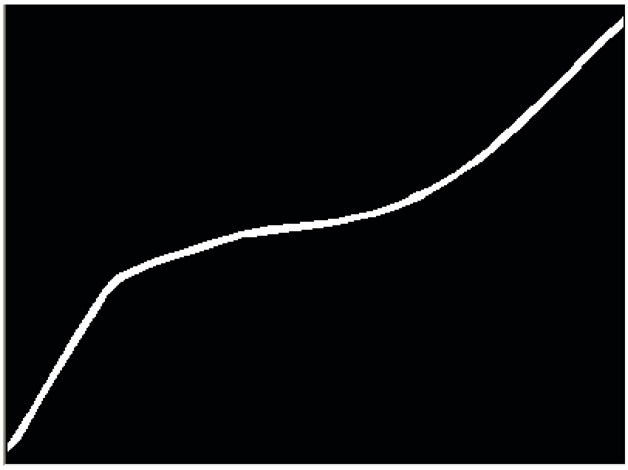

Figure 8. Visually extracted road.

4.2. Extraction of a road with obstacles

In the second experiment an image of a larger size (Fig. 9), which contains a road that is non-continuous due to the occurrence of occlusions caused by trees and shadows. It also has sinuous curves and access to other roads. Some other objects in the image are also, spectrally, very similar to the road.

Figure 9 shows the segments that were selected by the genetic algorithms. Two errors can be readily noticed. One is located on the center of the image and is due to the spectral confusion of the reference sample with another feature (bare soil) that lies next to the road. The second error (right) is related to the occlusions caused by a shadow. But, considering the other occlusion gaps, the presence of occlusion was not a problem for the algorithm.

The second experiment, using an image that shows several gaps and curves, proves that the solution found by the genetic approach is sub-optimal, but represents a good approximation of the actual road. Comparing the pixels that form the detected segment with the road that was defined by visual analysis, it was computed that from the total of 1517 detected pixels, 1269 are correct and only 248 are wrong. The error rate, therefore, was 16.3%.

The error rate increases proportionally to the number of obstacles and complexity of the road. Other experiments, accomplished in one of the thesis seminars by the same authors, not presented here, suggest that the error rate does not vary widely.

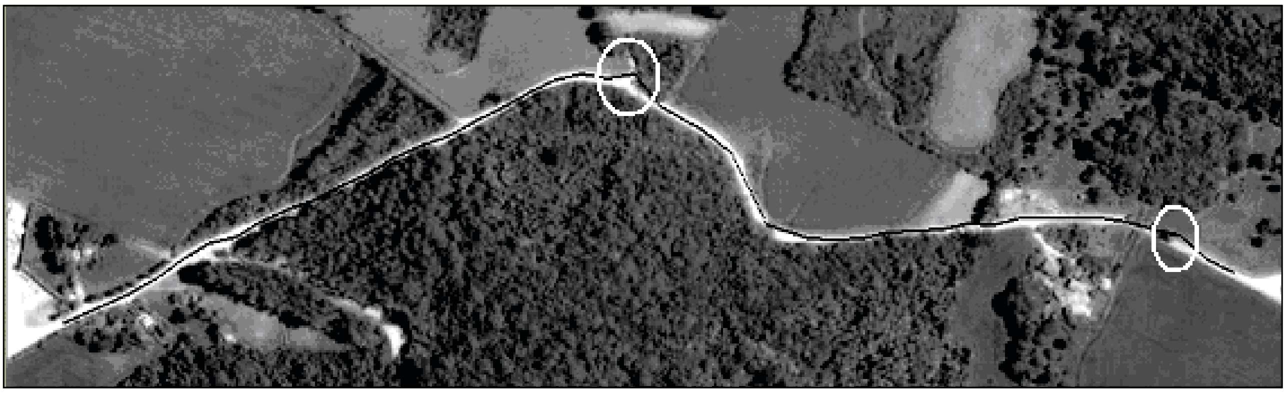

Figura 9. Trace of the segments detected (according to the experiment).

5. Conclusion

A semi-automated approach of road detection, based on genetic algorithms, was described. The key point in the proposed method is the proposal of a fitness function. Here, a fitness function based on geometric and spectral characteristics of roads was presented. The fitness function showed a good performance, even when the solution is sub-optimal.

The geometric factors of the fitness function are very important in the process. Therefore, they received higher weights, especially for straight roads. When a curve is analyzed, the spectral factor becomes important, because it avoids that the selected segments leave the road, discarding segments that are spectrally different from the road.

Finally, after a general analysis of the results, it is concluded that the method is promising. That is, in spite of the simplicity of the proposed methodology, the results are good and can be used to describe a road. They can also be improved, in a second phase by making a fine analysis of the detected segments. For example, the size of the segments can be reduced and the number of iterations increased.

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