DYNAMIC PROGRAMMING APPROACH FOR SEMI-AUTOMATED ROAD EXTRACTION FROM MEDIUM- AND HIGH-RESOLUTION IMAGES

A. P. Dal Poz*, G. M. do Vale

Dept. of Cartography, São Paulo State University, R. Roberto Simonsen 305, 19060-900 Presidente Prudente-SP, Brazil,
{aluir,gmvale}@prudente.unesp.br

Commission III, WG III/4

KEY WORDS: Dynamic Programming, Edge Analysis, Road Extraction, Vision, Semi-Automation

ABSTRACT:

This paper presents a dynamic programming approach for semi-automated road extraction from medium- and high-resolution images. This method is a modified version of a pre-existent dynamic programming method for road extraction from low-resolution images. The basic assumption of this pre-existent method is that roads manifest as lines in low-resolution images and as such can be modelled and extracted as linear features. Contrary to this, roads manifest as ribbon features in medium- and high-resolution images and the goal of road extraction methods becomes the road centrelines. As a result, the original method can not accurately extract road centrelines from medium- and high- resolution images. In view of this, we propose a modification of merit function of the original approach, which is carried out by a constraint function embedding road edge properties. Preliminary results demonstrate the modified algorithm's potential in extracting road centrelines from medium- and high-resolution images.

1. INTRODUCTION

Data acquisition for mapping and GIS (Geographic Information System) by photogrammetric techniques has traditionally been performed by manual extraction of cartographic features from images of the terrain surface ranging in scale from 1:3000 to 1:90000 (Sowmya and Trinder, 2000). Although this strategy is efficient under the viewpoints of accuracy and reliability, it is generally time-consuming and expensive, what certainly have limited the amount, resolution, and revision cycles of terrain information that can be extracted by using current digital photogrammetric systems. These systems allow the development of new automated or semi-automated techniques for capture and updating of GIS data, decreasing more and more the dependency of a human. In this context, road extraction has remained as an important issue of research.

Until now, fully automated systems for road extraction seem to be faraway from a mature state and, consequently, no such operational system is expected to be available in near future. With regard to semi-automated systems, probably some existing systems can already be used into operational work flows. Semi-automated approaches may be divided into two broad categories. The first includes road-following approaches, in which the road is sequentially traced by using only local road information (McKeown and Denlinger, 1988, Vosselman and Knecht, 1995, Dal Poz and Silva, 2002). These approaches are usually initialised by two close points on the road, being one a starting point and another a point to define the road direction. The second category includes active contour models (Kass et al., 1987, Neuenschwander et al., 1997, Gruen and Li, 1997, Agouris et al., 2000), simulated annealing (Trinder et al., 2000), and dynamic programming optimisation (Merlet and Zerubia, 1996, Gruen and Li, 1997), in which some type of simultaneous curve fitting is used. Usually, these approaches are initialised by a few seed points describing coarsely the road.

This paper presents a dynamic programming approach, which is a modified version of a pre-existent dynamic programming approach proposed in Gruen and Li (1997) and also reported in Dal Poz et al. (2000). Like some other pre-existent dynamic programming approaches (Fischler et al., 1981, Sakoda et al., 1993, Merlet and Zerubia, 1996), Gruen and Li's approach is more appropriated to extract road from low-resolution images, in which roads manifest as lines. In order to allow this method to accurately extract road centrelines from medium- and high-resolution images, we propose a modification of cost (or merit) function of the original approach. This modification was carried out in our approach by a constraint function embedding road edge properties. This allows the modified approach to treat the road as a ribbon feature. Other simultaneous curve fitting approaches modelling roads as ribbon features have been proposed, but they work according to the principle of energy minimisation. Examples are the LSB-Snakes (Gruen and Li, 1997) and the ziplok snakes (Laptev et al., 2000), being this last one used in the context of fully automatic road extraction.

The paper is organized as follows. Section 2 briefly presents the pre-existent dynamic programming approach. Section 3 presents the modified dynamic programming approach. In Section 4 is presented the experimental results. Finally, conclusions are provided in Section 5.

2. PRE-EXISTENT DYNAMIC PROGRAMMING APPROACH

The method consists basically in solving a generic road model by the so-called dynamic programming algorithm. Below we

* Corresponding author.

present a summary review of the approach. Details are found in Gruen and Li (1997).

2.1 Generic Road Model

A generic road model can be formulated taking into account photometric and geometric road properties (e.g.: road is elongated and lighter than the background, road grey levels do not change much within a short distance, road is smooth). Road properties are used to formulate a generic road model considering that the road can be represented by a polygon $P=\{p_1, ..., p_n\}$, where $p_i= (x_i, y_i)$ are the image co-ordinates of the i^{th} vertex. The generic road model can be formulated by the merit function (equation 1) and an inequality constraint (equation 2), as follows (Gruen and Li, 1997),

$$E = \sum_{i=1}^{n-1}((Ep_1(p_i, p_{i+1}) - \beta . Ep_2(p_i, p_{i+1}) + \gamma\, Ep_3(p_i, p_{i+1})).[1+\cos(\alpha_i - \alpha_{i+1})]/|\Delta S_i|) \tag{1}$$

$$= \sum_{i=1}^{n-1} E_i(p_{i-1}, p_i, p_{i+1})$$

$$C_i = |\alpha_i - \alpha_{i+1}| < T \tag{2}$$

where $Ep_1(p_i, p_{i+1})$, $Ep_2(p_i, p_{i+1})$, and $Ep_3(p_i, p_{i+1})$ are functions describing geometric and radiometric road properties and depending on consecutive points p_i and p_{i+1}

α_i is the direction of the vector defined by points p_{i-1} and p_i

β and γ are positive constants

$|\Delta S_i|$ is the distance between points p_{i-1} and p_i

T is a user-defined threshold for direction change between two adjacent vectors.

Analysing the merit function (equation 1), one can conclude that it is a sum of functions E_i depending only on three consecutive points (p_{i-1}, p_i, p_{i+1}) of the polygon *P*. In other words, each point (p_i) is directly related to the point before (p_{i-1}) and after (p_{i+1}) it. This enables to use dynamic programming algorithm to solve efficiently this problem through a sequential decision-making process (Gruen and Li, 1997).

2.2 Solution for the Generic Road Model

Figure 1 illustrates an iterative solution for road extraction by using dynamic programming algorithm. Figure 1(a) shows a short segment of a road, which is approximated by a polygon with 4 seed points. These vertices are usually provided by a human operator, as e.g. McKeown and Denlinger (1988) and Gruen and Li (1997). Alternatively, they may result from a road finding method (as in Zlotnick and Carnine (1993)), or by using information from maps or a GIS database (as in Agouris et al. (2000)). Figures 1(b) and 1(c) simulate how the first iteration is carried out. As shown in figure 1(b), one equidistant new vertex is interpolated linearly between every adjacent seed points, resulting in a 7-point polygon. Although this polygon is now described with more points, no new information about the road is added. Thus, the polygons of figures 1(a) and 1(b) are actually the same before the application of a dynamic programming algorithm. In the course of dynamic programming optimisation, every vertex may move around its initial position. For practical reasons, instead of using a 2D search window around each vertex, a 1D search window (see dashed lines in figure 1(b)) perpendicular to the initial polygon at every vertex is actually used. As a result, pull-in-range can be maintained, but with a lower computational complexity (Gruen and Li, 1997). In order to further decrease computational complexity, Gruen and Li (1997) also suggests to use search windows with different resolutions, i.e., the window elements can be computed in intervals of several pixels in the first iterations and smaller intervals in the last iterations. Another benefit of this procedure is the large pull-in-range. The result of application of dynamic programming algorithm to the points of figure 1(b) is illustrated in figure 1(c), which is a polygon closer to the given road's shape. Please note that figure 1(c) shows both the original points and the dynamic programming optimisation results (i.e., the polygon close to the road centreline).

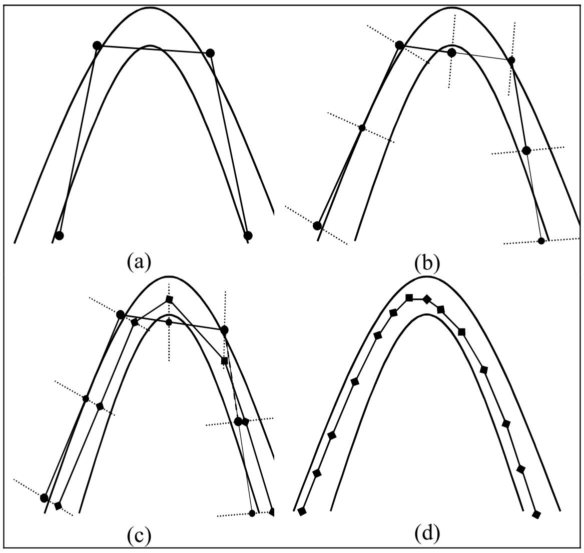

Figure 1. Iterative process for road extraction using dynamic programming

The process described above is iterated until all new computed points and neighbouring pre-existing vertices are within the collinearity threshold. The final result is illustrated in the figure 1(d). The obtained points maximise the merit function (equation 1) and satisfy the constraint $C_i<T$, i= 1, ..., n-1. Figure 1(d) also illustrates that the extracted road centreline does not necessarily coincide with the correct road centreline.

3. MODIFIED DYNAMIC PROGRAMMING METHOD FOR ROAD EXTRACTION FROM MEDIUM- AND HIGH-RESOLUTION IMAGE

The dynamic programming approach previously described is efficient for road extraction when the input data is mainly a low-resolution image. This type of image shows roads with 1-3 pixels width and, as a result, these roads can be modelled as linear features. Thus, at the end of dynamic programming optimisation process the resulting polygons will model accurately the respective roads. However, as for medium- and high-resolution images the goal of extraction methods is the road centreline, the optimisation process based on the merit function that is given by equation 1 does not allow good results to be obtained. This takes place because the resulting extracted feature corresponds to the maximum of merit function (equation 1) and is unlikely it coincides with the road centreline.

In order to embody road centreline definition in merit function given by equation 1, a modification based on road edge properties is proposed. Equation 1 shows that the merit function can be expressed in short as follows,

$$E = \sum_{i=1}^{n-1} E_i(p_{i-1}, p_i, p_{i+1}) \qquad (3)$$

The road centreline definition can be embodied in equation 3 by adding to this equation a constraint function based on a triple product among inner products of anti-parallel gradient vectors, i.e.,

$$E^m = \sum_{i=1}^{n-1}[E_i(p_{i-1}, p_i, p_{i+1}) - \langle \vec{V}_{i-1}, \vec{V}'_{i-1} \rangle . \langle \vec{V}_i, \vec{V}'_i \rangle . \langle \vec{V}_{i+1}, \vec{V}'_{i+1} \rangle] \qquad (4)$$

where, $\vec{V}_{i-1}$ and $\vec{V}'_{i-1}$, $\vec{V}_i$ and $\vec{V}'_i$, and $\vec{V}_{i+1}$ and $\vec{V}'_{i+1}$ are pairs of anti-parallel gradient vectors that are taken from road cross sections defined at points p_{i-1}, p_i and p_{i+1}, respectively (figure 2).

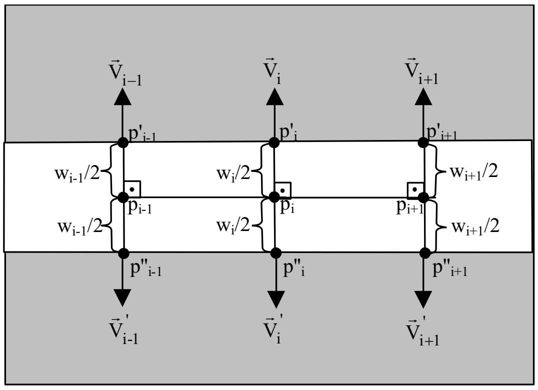

Figure 2. Segment of road centreline

Let $\vec{u}$ and $\vec{v}$ be two non-null vectors and θ be the angle between both vectors. Taking into account that the inner product between $\vec{u}$ and $\vec{v}$ is defined as $\langle \vec{u}, \vec{v} \rangle$ = $|\vec{u}|.|\vec{v}|.\cos\theta$, equation 4 can be rewritten as,

$$E^m = \sum_{i=1}^{n-1}[E_i(p_{i-1}, p_i, p_{i+1}) - |\vec{V}_{i-1}|.|\vec{V}'_{i-1}|.\cos\theta_{i-1}.|\vec{V}_i|.|\vec{V}'_i|.\cos\theta_i.|\vec{V}_{i+1}|.|\vec{V}'_{i+1}|.\cos\theta_{i+1}] \qquad (5)$$

Considering that the basic objective of dynamic programming optimisation process is to find the maximum of merit function, and that the first term of summation equation (equation 5) is positive, then the new term needs to add a positive quantity. Thus, the negative sign before new term is justified because $\theta_{i-1} \cong \theta_i \cong \theta_{i+1} \cong 180^o$, implying that $\cos\theta_{i-1} \cong \cos\theta_i \cong \cos\theta_{i+1} \cong -1$. Also considering that the magnitudes of gradient vectors at road edge points are local maxima, then the inner products between pairs of anti-parallel gradient vectors $\vec{V}_{i-1}$ and $\vec{V}'_{i-1}$, $\vec{V}_i$ and $\vec{V}'_i$, and $\vec{V}_{i+1}$ and $\vec{V}'_{i+1}$ are maxima too. In such a case, the new term of modified merit function takes an extreme value, enforcing points p_{i-1}, p_i and p_{i+1} to be accurately positioned on road centreline.

Although equations 4 or 5 express the basic principle of modified merit function, it is not in appropriate form to better understand the dynamic programming optimisation based on modified merit function. Figure 2 shows a segment of road centreline defined by consecutive points p_{i-1}, p_i and p_{i+1}. Gradient vectors $\vec{V}_{i-1}$, $\vec{V}'_{i-1}$, $\vec{V}_i$, $\vec{V}'_i$, $\vec{V}_{i+1}$, and $\vec{V}'_{i+1}$ are taken, respectively, at road edge points p'_{i-1}, p''_{i-1}, p'_i, p''_i, p'_{i+1}, and p''_{i+1}. The co-ordinates of these points are easily expressed in function of points p_{i-1}, p_i, and p_{i+1}, and also in function of local road widths (w_{i-1}, w_i, and w_{i+1}) at same points. This is accomplished in such way pairs of points p'_{i-1} and p''_{i-1}, p'_i and p''_i, and p'_{i+1} and p''_{i+1} are symmetrically positioned in relation to points p_{i-1}, p_i, and p_{i+1}, respectively. Moreover, the distances between every road centreline point (e.g., p_i) and respective road edges points (p_i' and p_i'') are one-half of the local road width (w_i) (figure 2). As can be noticed below, the road centreline points and respective local road widths are the unknowns to be determined in optimisation process by dynamic programming algorithm. Representing the constraint function (second term of summation equation, i.e., equation 4) as E_i^p, the following expression can be written,

$$\langle \vec{V}_{i-1}, \vec{V}'_{i-1} \rangle . \langle \vec{V}_i, \vec{V}'_i \rangle . \langle \vec{V}_{i+1}, \vec{V}'_{i+1} \rangle = E_i^p(p_{i-1}, p_i, p_{i+1}, w_{i-1}, w_i, w_{i+1}) \qquad (6)$$

Equation 6 shows that the constraint function (E_i^p) for a road segment defined by points p_{i-1}, p_i, and p_{i+1} depends on only the co-ordinates of these points and local road widths at these same points. Taking into account equation 6 in equation 4, this last one can be rewritten as follows,

$$E^m = \sum_{i=1}^{n-1}[E_i(p_{i-1}, p_i, p_{i+1}) - E_i^p(p_{i-1}, p_i, p_{i+1}, w_{i-1}, w_i, w_{i+1})] \qquad (7)$$

Now substituting both terms under summation symbol of equation 7 by $E_i^t(p_{i-1}, p_i, p_{i+1}, w_{i-1}, w_i, w_{i+1})$, we get,

$$E^m = \sum_{i-1}^{n-1} E_i^t(p_{i-1}, p_i, p_{i+1}, w_{i-1}, w_i, w_{i+1}) \qquad (8)$$

which is the full form of the modified merit function. Notice that, as in the case of the merit function given by equation 3, the modified merit function does not interrelate simultaneously all variables (i.e., point co-ordinates of road centreline and local road widths). This enables dynamic programming algorithm to be used in an efficient manner in optimisation process based on the modified merit function. However, this equation can be simplified, in order to significantly reduce the computational complexity of optimisation process. Tanking into account that road width does not vary too much, especially along a short road segment, a valid supposition is that $w_{i-1} \cong w_i \cong w_{i+1}$. This is more realistic after several iterations are carried out, because the road centreline is progressively refined and made denser. In other words, the road segment defined by three consecutive points (i.e., p_{i-1}, p_i, and p_{i+1}) is shortened in progress of dynamic programming optimisation, becoming unnecessary the adoption of different road widths along local road segments. In fact, this is also true for whole optimisation process, as possible biases at the beginning of optimisation process can be corrected at last iterations. Thus, the final form of modified merit function can be written as,

$$E^m = \sum_{i-1}^{n-1} E_i^t(p_{i-1}, p_i, p_{i+1}, w_i) \qquad (9)$$

Equation 9 shows that only seven unknowns are interrelated simultaneously, against six in merit function given by equation 3. The dynamic programming optimisation based on equation 9 follows the same principle briefly described in Section 2.2.

4. EXPERIMENTAL RESULTS

The approach previously described was implemented on a PC environment using Borland C++ computer language. Until now, the software does not have any graphical interface to assist the operator in supplying the necessary information (e.g., seed points) to initialise optimisation process. The seed points are collected by an available commercial software and supplied, together with other information (e.g., parameters for initialising the Canny edge detection routine), via ASCII files to the extraction system. In order to experimentally evaluate the potential of the method, two experiments are carried out using one medium-resolution image and another one, high-resolution image. Below we present and discuss the results.

First experiment is carried out with the medium-resolution image (500 x 500 pixels), which shows two main roads with average road width of 5 pixels. Figure 3 presents results obtained by dynamic programming optimisation using modified merit function. To make easier the visual analysis of results, the extracted road centrelines are overlaid in black on the image. The seed points used to initialise the extraction process are also overlaid on the image.

The results obtained (figure 3) using modified dynamic programming method are satisfactory, as the two road centrelines are accurately extracted. However, the road centrelines are slightly perturbed where one or both road edges are missed. This takes place on road 2, where this road meets road 1 and both edges are missed. Another example occurs along a road segment of road 1, where a long road edge is missed. It is also noticed that minor road edge perturbations along roads do not influence the performance of the method. Therefore, this test image shows that the modification of merit function allows accurate road centreline to be extracted, but the optimisation process becomes slightly sensitive to larger edge perturbation.

In order to numerically determine the accuracy of modified method road centrelines were manually extracted and numerically compared to corresponding ones extracted by the road extraction algorithm. The node positions of road centrelines were determined to be about 0.5 pixels from the manually extracted road centreline, which characterised a sub-pixel accuracy.

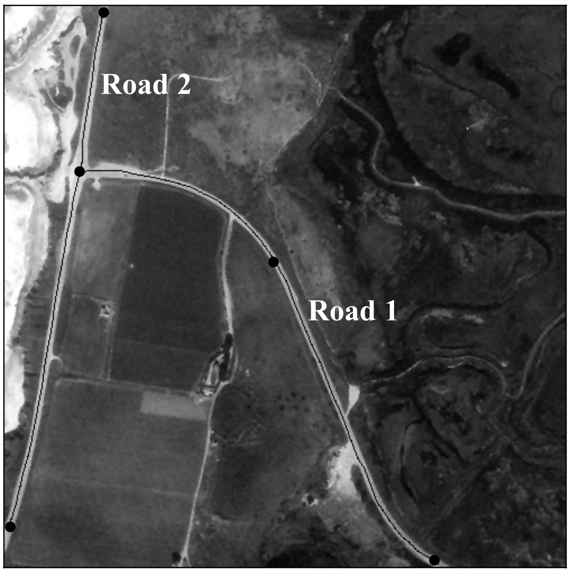

Figure 3. Results obtained using modified merit function for test image 1

Second experiment (figure 4) is carried out with the high-resolution image (500 x 600 pixels), which shows three main roads with average road width of 15 pixels, being one of them very short (i.e., Road 3). Figure 4 presents results obtained by dynamic programming optimisation using modified merit function. This test image shows several perturbations along roads caused by trees occluding partially or almost totally the road and by a few road exits to secondary roads, where short road edges are missed. As in previous experiment, the seed points used to initialise the dynamic programming optimisation are also shown on this test image.

Figure 4 shows that the road centrelines extracted by dynamic programming optimisation based on modified merit function are in general very accurate. The exception is the short road centreline that belongs to the Road 3 extracted from the road crossing region between Road 2 and Road 3. This can take place as in road crossings the edge constraint term almost vanishes. As for this case the optimisation process is not expected to significantly correct the position of seed point supplied on that road crossing, that extraction problem could be minimised with a proper selection of one out of two seed point for Road 3, as e.g. close to geometric centre of road crossing between Road 2 and Road 3. This image also shows that the extracted road centrelines are not significantly influenced by obstacles and small road edge perturbations along the roads. As a result, the extracted road centrelines look like smooth curves.

The numerical comparison between the manually extracted road centrelines and the corresponding ones extracted by the algorithm based on modified merit function shows that the average distance between them is about 0.7 pixel. Again, a sub-pixel accuracy is obtained.

Figure 4. Results obtained using modified merit function for test image 2

5. CONCLUSIONS

In this paper was presented a semi-automated method for road extraction from medium- and high-resolution images. The proposed methodology results from the modification of a dynamic programming approach for road extraction proposed by Gruen and Li (1997). The modification was accomplished in merit function by adding a constraint function embedding edge road characteristics. The major goal of this modification is to allow the road centrelines to be accurately extracted by the modified dynamic programming approach.
The modified approach was evaluated using two real images, being one of medium-resolution and another one of high-resolution. Both test images presented roads affected mainly by either missing road edges or occlusions resulted from trees. In general, the experiments showed that the approach is robust and accurate in extracting the road centrelines. However, longer missing road edges displayed in first test image (figure 3) caused a slightly changing in direction of road centrelines. As a result, the road centrelines extracted by modified approach are not so smooth. Related to the perturbations caused by trees, which obstruct partly or almost totally the roads (figure 4), no significative influence is observed in results obtained by modified approach. This occurs because gradient vectors are usually no longer anti-parallel at points related to occluded regions and, as a result, the edge constraints for these points almost vanish. In other words, the modified approach can handle situation involving partially or totally occluded regions. The extraction problem observed on road crossing between Road 3 and Road 2 (figure 4), where a short road segment of Road 3 was not accurately extracted, was also caused by the lack of anti-parallel edges for Road 3 in that region. Finally, our general conclusion is that the modified approach clearly exhibits appropriate performance for the test images used in experiments.

6. ACKNOWLEDGEMENTS

This work was supported by FAPESP (Research Foundation of the State of São Paulo, Brazil) grant number 01/01168-5 and CAPES (Brazilian Foundation for Support of Graduate People).

7. REFERENCES

Agouris, P., Gyftakis, S., Stefanidis, A., 2000. Uncertainty in image-based change detection (snakes). In: *Accuracy 2000*, Amsterdam, Netherlands, pp. 1-8.

Dal Poz, A. P., Gyftakis, S., Agouris, P., 2000. Semi-automatic road extraction: Comparison of methodologies and experiments, In: *DC 2000 ASPRS Annual Conference*, CD-ROM, Washington-DC, USA.

Dal Poz, A. P., Silva, M. A. O., 2002. Active testing and edge analysis for road centreline extraction. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, v. 34, part B, Graz, Austria, pp. 44-47.

Fischler, M. A., Tenenbaum, J. M., Wolf, H. C., 1981. Detection of roads and linear structures in low-resolution aerial imagery using a multisource knowledge integration technique. *Computer Graphics and Image Processing*, v. 15, pp. 201-223.

Gruen, A., Li, H., 1997. Semi-automatic linear feature extraction by dynamic programming and LSB-snakes. *Photogrammetric Engineering and Remote Sensing*, 63(8), pp. 985-995.

Kass, M., Witkin, A. Terzopoulos, D., 1987. Snakes: Active contour models. In: *First International Conference on Computer Vision*, London, UK, pp. 259-268.

Laptev, I., Mayer, H., Lindeberg, T., Eckstein, W., Steger, C., Baumgartner, A., 2000. Automatic extraction of roads from aerial images based on scale space and snakes. *Machine Vision and Applications*, 12(1), pp. 22-31.

McKeown, D. M., Denlinger, J. L., 1988. Cooperative methods for road tracking in aerial imagery. In: *Workshop of Computer Vision and Pattern Recognition*, pp. 662-672.

Merlet, N., Zerubia, J., 1996. New prospects in line detection by dynamic programming. *IEEE Transaction on Pattern Analysis and Machine Intelligence*, 18 (4), pp. 426-431.

Neuenschwader, W. M., Fua, P., Iverson, L., Szekely, G., Kubler, O., 1997. Ziplock snakes. *International Journal of Computer Vision*, 25 (6), pp. 191-201.

Sakoda, B, Hu, J., Pavlids, T., 1993. Computer assisted tracing of faint roads in satellite images. In: *ASPRS-ACSM Annual Convention*, v. 2, New Orleans, USA, pp. 311-323.

Sowmya, A, Trinder, J., 2000. Modelling and representation issues in automated feature extraction from aerial and satellite images. *ISPRS Journal of Photogrammetry and Remote Sensing*, 55(1), pp. 34-47.

Trinder, J. C., Maulik, U., Bandyopadhyay, S., 2000. Semi-automated feature extraction using simulated annealing. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, v. 33, part B3, pp. 905-911.

Vosselman, G., de Knecht, J., 1995. Road tracing by profile matching and Kalman filtering. In: *Automatic Extraction of Man-Made Objects from Aerial and Space Images*, Birkhaeuser Verlag, pp. 265-274.

Zlotnick, A., Carnine, P.D., 1993. Finding roads seeds in aerial images. *CVGIP: Image Understanding*, 57(2), pp. 243-260.