

CONTOUR LINE GENERALIZATION BY MEANS OF ARTIFICIAL INTELLIGENCE TECHNIQUES

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SUMMARY

The cartographic generalization of contour lines have been extensively studied and several algorithms have been proposed. Nevertheless, most of algorithms are human dependent and time consuming.

The great difficulty in the automation of cartographic generalization resides in the transposition of a cognitive procedure, which analyzes and decides how and where to generalize, in every concrete situation, based on acquired knowledge throughout decades of evolution and training, to a computational one.

In this paper, a new methodology is presented for contour line generalization. The method is based on the combination of artificial neural network, decision tree and classification & regression tree techniques into an Agent system where the “best” parameter for contour line generalization is selected. The contour line is generalized using a tension parameter in analogy with the tension-extension of materials with linear elasticity. The tension parameter is locally adapted to a selection set of line characteristics. The proposed methodology determines the tension to be applied to the curve in function of each contour line characteristics (including the fractal dimension and the length).

1. INTRODUCTION

Line simplification, from the cartographic point of view, is a simplification of a shape required to represent a feature. The essential point of this method is the removal of unnecessary line details without destroying its essential shape. For this reason, simplification algorithms do not always operate well on all lines or on the different shaped parts of a specific line.

Line generalization can be considered as one of the most complex processes in cartographic production since it depends on factors such as the rate of scale change, the purpose of the map and the character of the cartographic line “Nakos, et al. 2008”.

Some methodologies proposed by researchers include segmentation methods that split up complex objects into homogeneous parts. The application of the same algorithms with the same parameters to these parts of a line should yield the same results.

The aim of the algorithm presented here is to generalize contour lines, thus allowing them to be represented in smaller scale cartography. This algorithm simulates the operations of simplification and smoothing carried out by cartographers. However this algorithm is not adapted to the generalization of some artificial features such as houses, for example.

“Li et al., 1999” had generalized the Digital Terrain Model and obtained the line contours from the generalized model. The advantage of this approach is that there will be a guarantee of no intersections between contours.

Generalization requires a holistic vision of all processes and all areas, this is difficult due the way the data are manipulated and stored in Databases, the way that these are searched and also the way that the algorithms transform these data. If the algorithmic solution does not exist, every effort of segmentation and classification could have been done in vain.

In this paper we propose a knowledge-based method for line generalization using artificial intelligence. The purpose is the generalization of contour lines of medium scale maps (1:25k scale). The line is generalized using a tension parameter in analogy with the tension-extension of materials with linear elasticity. The tension parameter is locally adapted to a selected set of line characteristics: fractal dimension, length, ...etc.

2. THE METHODOLOGY

A chart at 1:25k scale was used for training the artificial neural network, and built the decision tree and the classification & regression tree. A set of contour lines (248 contour lines) were interactively generalized by a cartographer editor using the algorithm and the tension parameter. We characterize these lines with a set of classical measurements (fractal dimension, length, number of points, etc..). All these data, the value of the tension and the properties of each line, were used to train the artificial intelligence algorithms. Many learning techniques exist that do have different properties. Our choice here is to apply different ones and to compare the result according to confidence factors. Four solutions were built. The first uses the artificial

neural network, the second the decision tree, the third the classification & regression tree and the fourth the combination of the above by means of a specific Agent which choose the best value from the three techniques.

The goal of the process is to find the appropriate value of the algorithm presented here. The search for the parameter values is done by means of supervised learning techniques.

After finishing the learning process these results were applied to other maps of the same series. These results have been verified by an experienced cartographer who validated the process, see Werschlein and Weibel (1994), “Lagrange, et al. 2000” about the use of neural nets in cartographic generalization.

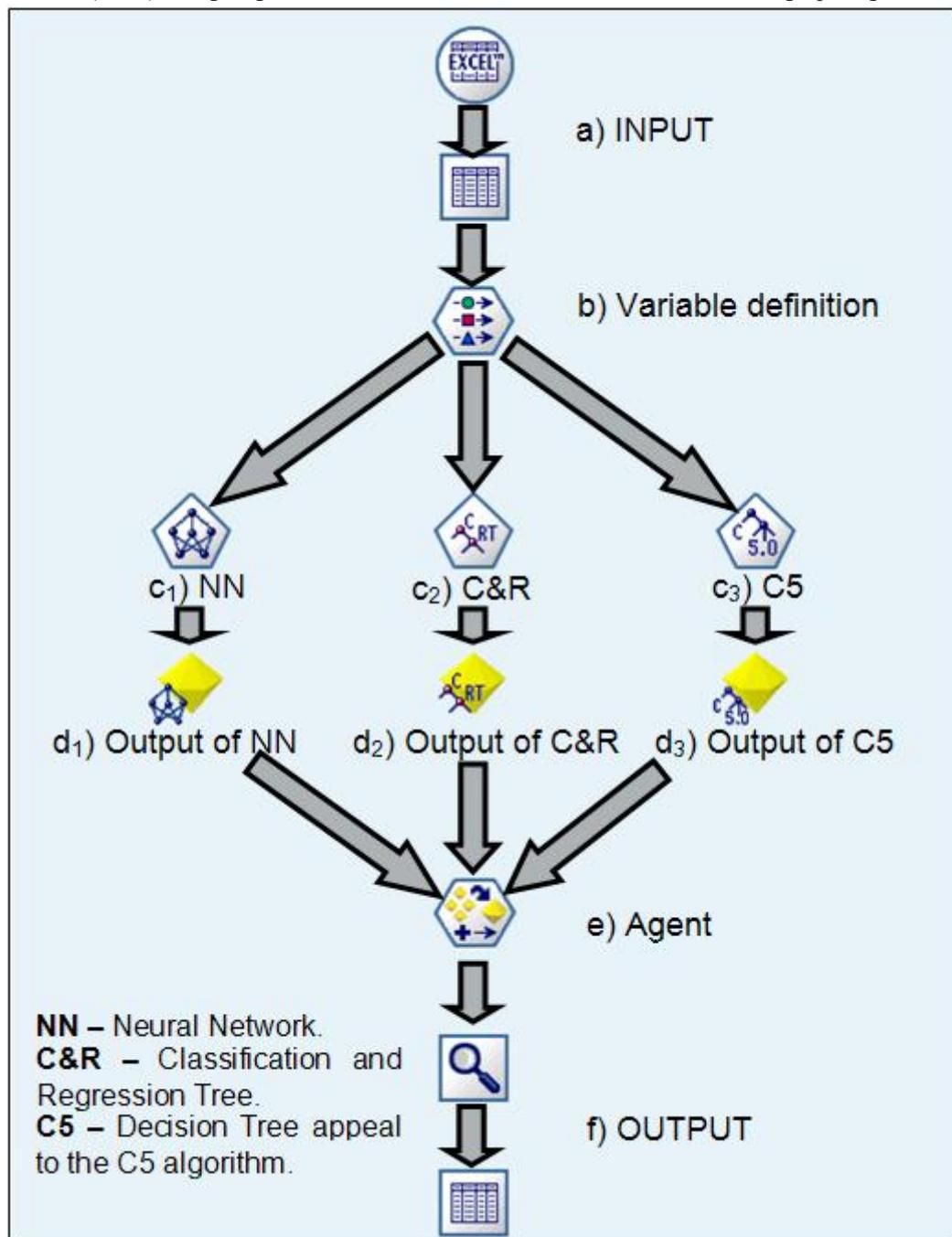


Figure 1 – General project of activities in Artificial Intelligence

The first step includes the data preparation, the variable definition and their respective domains, including the characterizer attributes for each contour line of input, figure 1 a) and b). Here is defined the Output variable, where the values of the tension for each method of AI are kept.

This data is then connected to the AI methods, with the parameters that have been previously refined during the learning process. In any other of these methods the output variable corresponds to the tension be used in the generalization algorithm, see figure 1 d1) d2) and d3).

It is frequent to integrate Neural Nets with other systems or paradigms to get solutions of more complex problems, as for example, in the area of Robotics. As the generalization is a complex process, we combine these techniques to obtain the prediction of the parameter tension to apply in the algorithm.

The results of these three methods are combined in an agent responsible for an “auction” in order that the thus calculated tension is the “best” one of the resultants of the three methods. Combining predictions of multiple methods, the limitations of these individual methods can be prevented, having as result a higher final accuracy, see figure 1 e). Based in the attributes of the contour lines, it was possible to predict the value to use in the generalization algorithm, see figure 1 f).

2.1 Algorithm for line generalization with tension

The algorithm presented here is the result of a careful observation and analysis of the manual operations of generalization, as carried out by experienced operators. During some time the operations of generalization of contour lines were analyzed and compared, as were the diverse versions of the same contour line, produced by different operators.

The chosen analogy, with the physical process, and the one that better describes the thought applied to this algorithm, is that of a deformable elastic body, to which a system of forces is applied that deforms it, where the tension is proportional to the applied deformation.

We assume that a contour line is the limit of a bidimensional, elastic and isotropic body, which is subjected to a system of forces. This body is deformed in order to reduce the relative maximums, approaching them to the centroid of the body, and to increase the relative minimums, moving them away from the centroid.

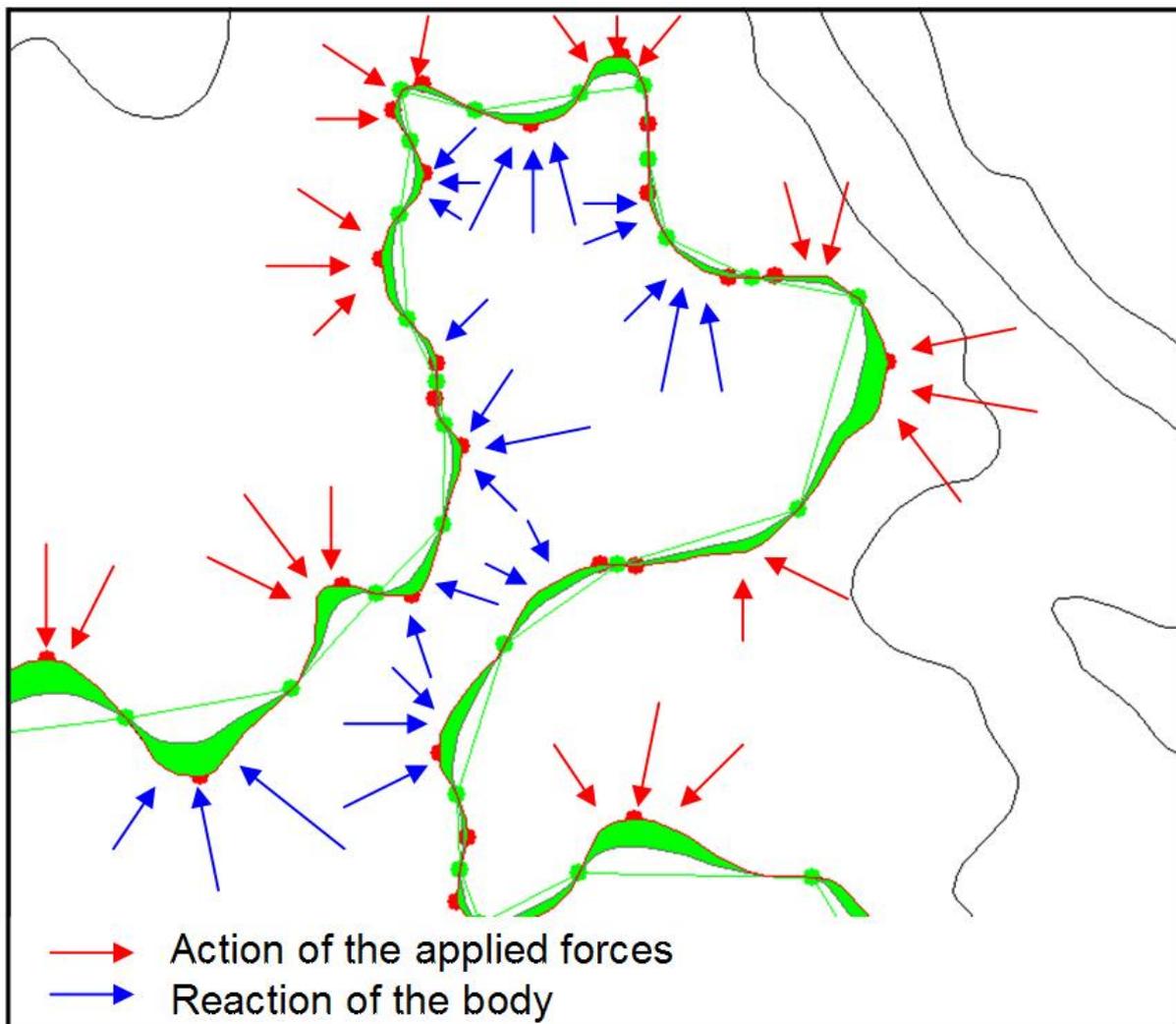


Figure 2 – Action and reaction of the line contour to the applied system of forces

The algorithm executes 5 consecutive steps for each contour line, as follows:

1st step – To compute the maximums and minimums (Max, Min);

2nd step – Between each maximum and minimum to calculate the average point, (M);

3rd step – To compute the vector

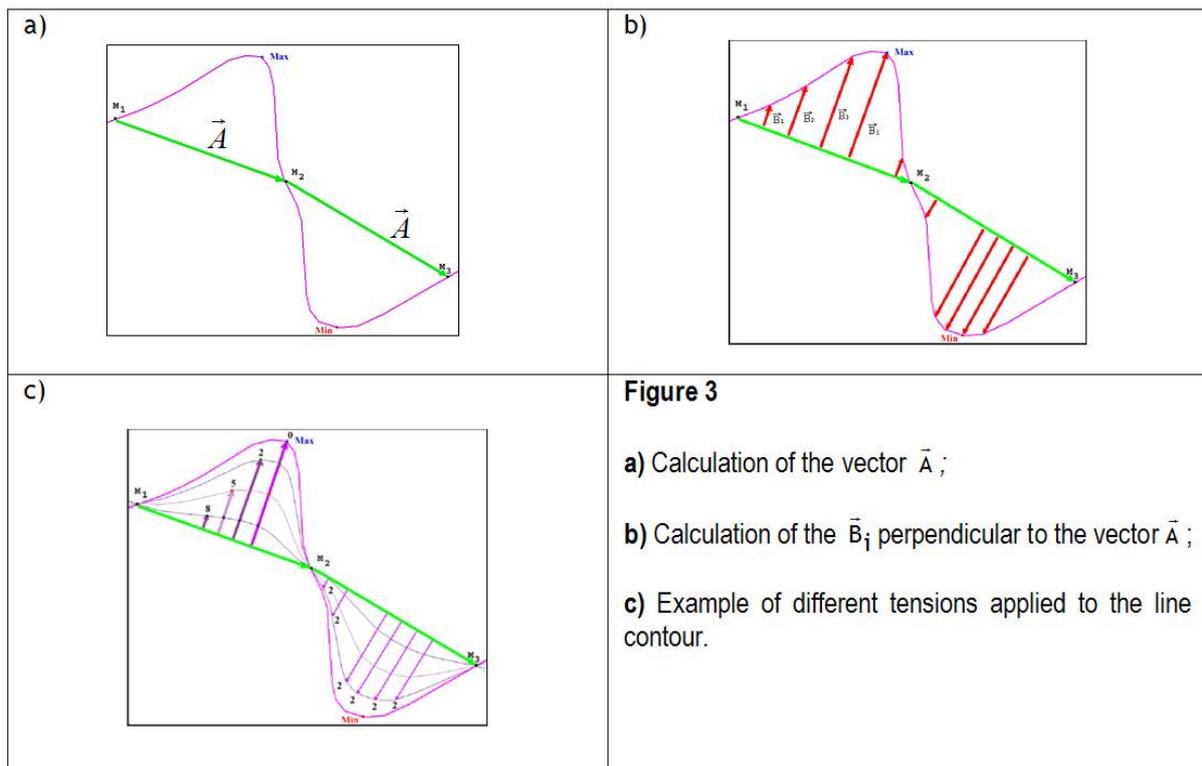
$$\vec{A} \left(\vec{A} = \overrightarrow{M_i M_{i+1}} \right);$$

$$\vec{B}_i \perp \vec{A}$$

4th step – To calculate the \vec{B}_i vectors perpendicular to the \vec{A} vector, between this and the vertices of the contour line;

$$\vec{B}_i$$

5th step – In accordance with the tension to apply, to reduce the norm of the vectors \vec{B}_i , and to calculate the new coordinates of the contour line vertex.



3. CONTOUR LINE CHARACTERIZATION

The characterization of lines is essential in the process of automatic generalization. To be efficient we have to find the optimal number of measures.

The angularity or the fractal dimension cannot by itself characterize lines, nor so any another set of characteristics. It can not distinguish for all type of lines, covers all the situations that we might face. The set of characteristics must be adjusted to the type of lines and purpose of the map. Most of the lines are not of a homogeneous nature, and can drastically change in the middle of their course.

Plazanet in Ruas (2002) describe the characterization and segmentation of roads based on this hierarchic method in tests of complexity and homogeneity of the lines. The method was implemented in the PlaGe platform, Plazanet, (1996). This method, start to detect characteristic points of the line to their

segmentation and analysis, such as: discontinuities in curvature, start or end points, maxima of curvature (vertices) and minima of curvature or inflection points and critical points chosen between the inflexion points. Further information can be seen on Plazanet (1995), Battersby and Clarke (2003).

McMaster (1986) defined 7 categories: line length, coordinate value, angularity, curvilinearity, vector difference, polygon difference and perimeter according with the information type that is under analysis. Jasinski (1990) suggested the following parameters: average segment length and their standard deviation, average of the distance between the original line and the generalized one and also their standard deviation, average of the angularity and their own standard deviation, curvilinearity ratio and Fractal Dimension. Bernhardt (1992) uses the following characterizing parameters: Richardson Plot, Fractal Dimension, Angularity, Curvilinearity ratio and displacement from the baseline.

In this paper some of the above mentioned parameters were considered and complemented with the curve fractal dimension and curve height. The parameters used were:

- Fractal dimension;
- Angularity;
- The number of vertices;
- Average of the segments length;
- Standard deviation of the segments length;
- Length of the line;
- Altimetry.

4. AL TECHNIQUES

The tension to be applied to a curve line depends on the characteristics of the line. The relation between a selection set of curve line characteristics and the tension parameter is determined by a knowledge-based method.

By applying this tension the line becomes simpler, have in this way a decreasing of their fractal dimension.

A neural network is a set of basic processing units called neuron or nodes. These neurons are tied by connections or synapses where the weight of the connection determines the intensity of a linkage and it is expressed by a numerical value. The knowledge of a neural network is built from the results of the learning process and is stored in the connections. After the training, the neural net is able to answer, in a short period of time, to new situations Costa (2004). An iteration of the algorithm of training is composed by adjustments of the weights of the connections for all the cases of training Russel (2003), see figure 4.

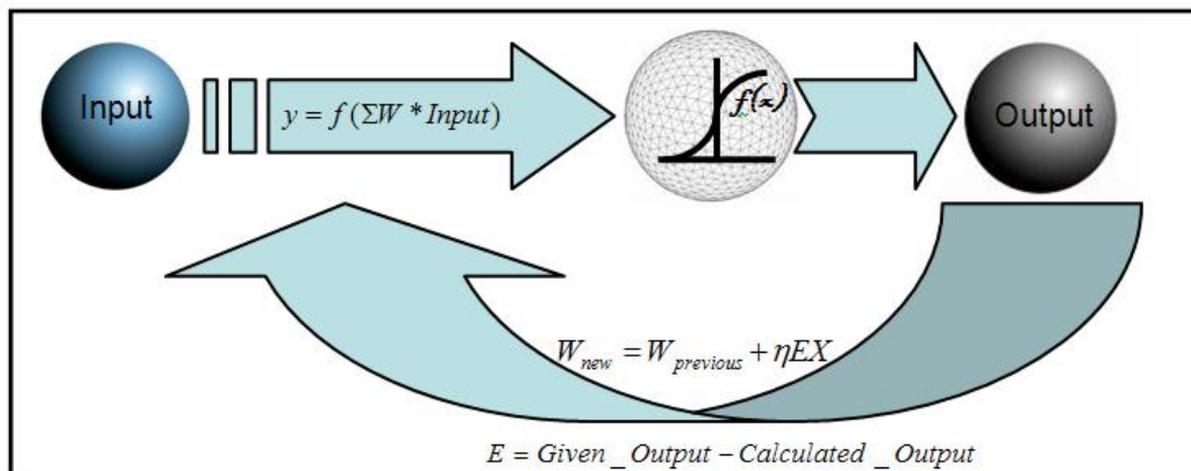


Figure 4 – Trainings of the Perceptron

The topology of the neural net is related to the way the different neuron connects among themselves. Neural architectures are typically organized in layers, see figure 6, with units that can be connected to the units of the previous layer.

The layers are classified in three groups:

- Input Layer: where the lines classifying attributes, are presented to the net;
- Intermediate or Hidden Layers: it is the place where most of the processing is made, through the weighted connections;
- Output Layer: the final result is finalized and presented.

4.2 Decision Trees

Decision trees are statistical models that use supervised training for the classification and foresight data. In its construction a training set is used constituted of inputs and outputs, where the outputs are the intended class.

A complex problem is decomposed in simpler sub-problems and this technique is recursively applied to each sub-problem. The discrimination capacity of a tree comes from the division of the space defined by the attributes in sub-spaces, and each sub-space is associated to a class Rich (1991).

The data is divided in two subgroups in a way that within each group the registers are more homogeneous than in the preceding group. This is a recursive process, and is repeated until the criterion of homogeneity or some other criteria to stop the process is achieved. The same field of the predictor can be used several times in different levels of the tree.

The most popular system is ID3. We use C5 for knowledge acquisition, an amelioration of the ID3 algorithm.

The figure 5 represents a decision tree where each decision knot contains a test for some attribute, each descending branch corresponds to a possible value of this attribute.

The more known criteria of partition are based on the entropy, for more information about this subject in generalization see for example "Plazanet, et al. 1998".

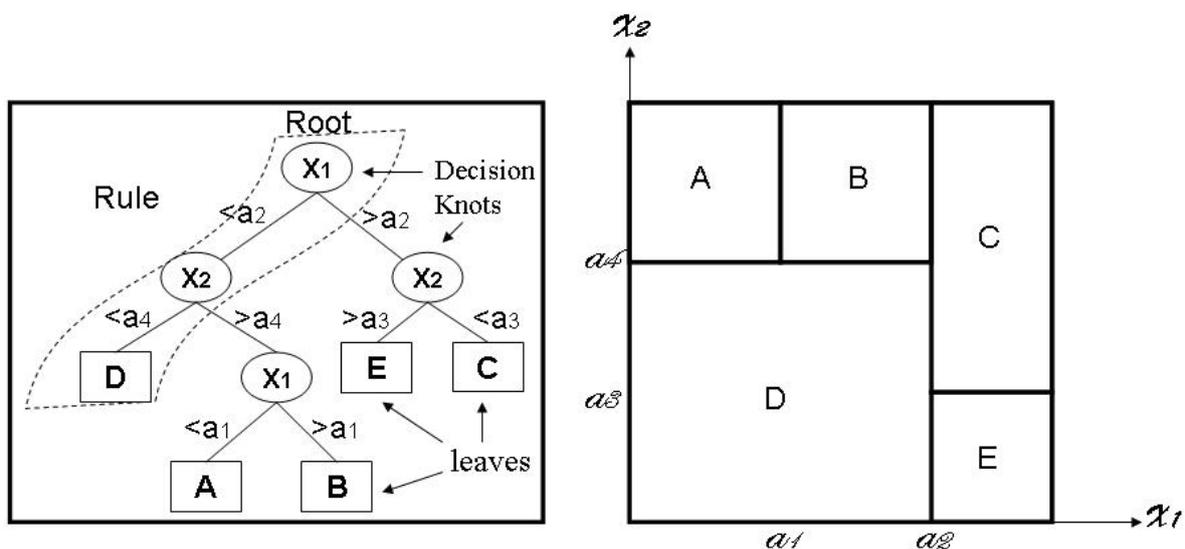


Figure 5 – Representation of a decision tree and its respective representation in the space

4.3 – CART Algorithm

The letters CART means (Classification And Regression Trees). These trees can be used not only to classify entities in one number of discrete groups, but also as an alternative approach to the analysis of regression in which the value of the answer (dependent variable) can be estimated. In our case the Tension to be used in the algorithm is the dependent variable that we intend to obtain as a function of a set of independent variables, for example fractal dimension, angularity, number of vertices.

CART can easily use both variables, numerical and categorical. Among others advantages of the method CART are its robustness to outliers.

The tree construction process starts dividing the sample or "the root node" in binary nodes based in a very simple question in the domain of the independent variables, with a answer of the type "yes" or "no".

Initially, all observations are placed in the root node. This node is impure or heterogeneous, since that contains values of possible tensions to be used in the algorithm. The goal is to arrange a rule that initially splits these values and create groups or binary nodes that they are internally more homogeneous than the root node.

Starting with the first variable, the method CART splits the variable in all the possible split points. In each possible split point of the variable, the sample is broken in two binary or children nodes. Case of an answer "yes" to the question is sent for a knot and answers "no" sent to the other node.

The objective is to maximize the reduction in the heterogeneity degree. CART attributes then classes to these nodes in accordance with a rule that minimizes the misclassification. Obviously, such a tree will have a large number of terminal nodes that are either pure or very small in content Yohannes (1999).

The next step is a process called pruning the tree, where the tree becomes smaller, better working in new situations and of a more generic form.

4.4 The Agent

The estimated parameter to use in the generalization algorithm was made by applying these three AI methods. In the case of a conflict, where each method of AI gives a different value to be used for the same line contour: What's the value to use?

To choose the one of the three solutions for each contour line, an agent was used who carries through an auction where the "best" parameter is chosen.

Abstractly, an auction takes place between an agent known as the auctioneer and a collection of agents known as the bidders. The goal of the auction is for the auctioneer to allocate the good to one of the bidders.

The agent that bids the most is allocated the good. Such protocols are known as first-price auctions. Another possibility is to allocate the good to the agent that bid the highest, but this agent pays only the amount of the second highest bid. Such auctions are known as second-price auctions. The simplest possibility is to have a single round of bidding, after which the auctioneer allocates the good to the winner. Such auctions are known as one shot. There are various types of auctions, English auctions, Dutch auctions, First-price sealed-bid auction and Vickrey auctions, see Wooldridge (2002).

The auction used in this project is of the type single round, the good is allocated to the highest price. The auctioned good is the tension to use in the respective line contour, the winner will be the method for that curve presenting the highest confidence, or either that in its learning process presents the highest probability of success.

5. EXPERIMENTS

5.1 Test Data

The contour lines of a map at scale 1/25k, had been used, in a total of 248 lines, for construction of the model and training the neural network.

Contour lines used in learning process enclose a large set of forms, as we can see in table 1 therefore its fractal dimension varies of 1.049 to 1.577, it also means that its sinuosity goes since the almost plain curve until very sinuous, the number of vertices varying between 10 and 11339 conjugated with the line length, average of the segments and standard deviation is indicative of its complexity, leading to conclude that the set of lines used is comprise and demonstrative.

Table 1 - Statistics of the line characterization

Parameter	Min	Max	Median	Average
Fractal dimension	1.049	1.577	1.361	1.351
Number of vertices	10	11339	77	475
Length of line(m)	50.7	107383.5	700.8	4575.1
Angularity (deg)	5.2	34.0	9.6	10.0
Average of Segments (m)	4.9	13.4	8.8	9.0
Standard deviation of segments (m)	4.1	698.1	48.1	86.9
Elevation of contour lines (m)	100	500	240	265

5.2 Training

An experienced operator has selected the optimal tension to be applied to each contour line in order to be generalized from 1:25k to 1:50k scale. Two sets of contour lines were processed: the first to train the algorithm and the second to evaluate the quality of the generalization process. The first set of contour lines are from sheet number 309 series M888, scale 1/25k and have 248 contour lines, the second set is from sheet number 50 of the same series and have 292 contour lines.

We used a Neural Network with three hidden layers. In the input layer it was read the attributes of the contour lines, and their own tension values that are obtained by the cartographer for each line. To improve the performance of the Neural Network the type and the value of the activation function was adjusted for a sigmoid of 0.5. We also selected 3 hidden layers, for these ones we obtained the best results.

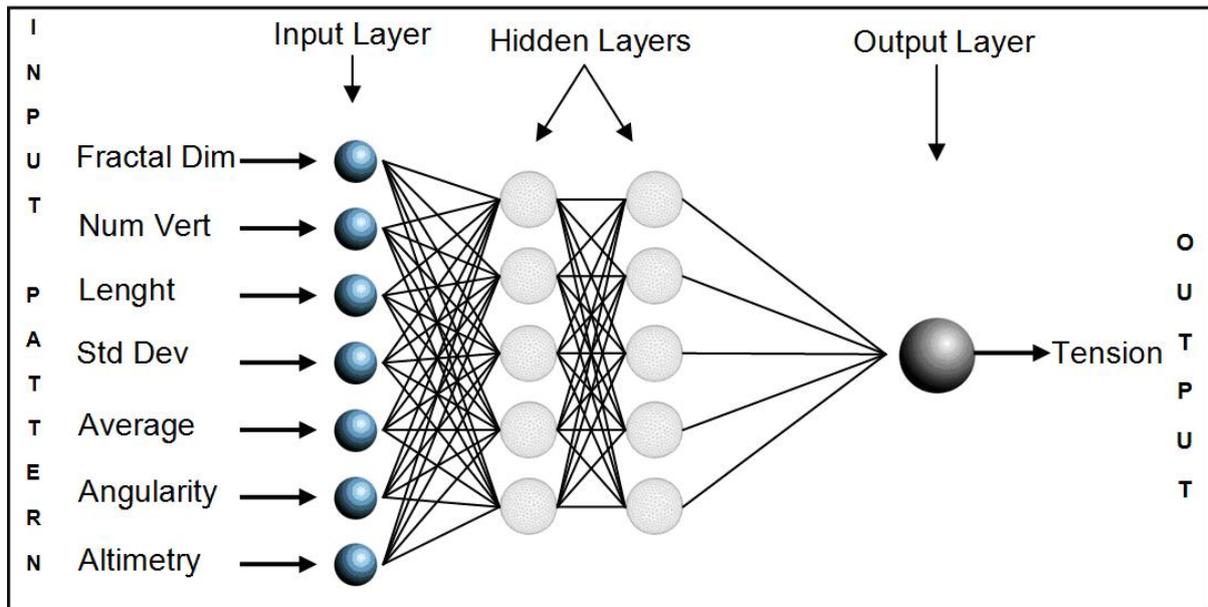


Figure 6 – Neural Network, organization in layers

In the output layer the value of the parameter (tension) is presented to be used by the algorithm.

Table 2 – Variable importance to the classification process

Variable importance	C&R	C5	Neur_Net
Fractal dimension	0.642	0.697	0.314
Average of Segments	0.243	0.041	0.198
Angularity	0.083	0.115	0.109
Elevation	0.017	0.042	0.090
Length of the line	0.008	0.000	0.117
Standard deviation of segments	0.008	0.093	0.069
Number of vertices	0.000	0.012	0.104

Analyzing the table 2 we can observe that for any of the methods the fractal dimension is the one that presents the biggest importance for the classification, the number of vertices and the length of the line do not influence this classification greatly.

In our case we used a tree with a depth of 8, any pruning was not applied, and it did not have any treatment to the surrogates' level, the number of cases is not excessively large and all the attributes are filled not having empty or null attributes.

The classes used for the supervised learning were the tension possible values used in the line contour generalization algorithm presented here.

5.3 Results

The quality of the proposed methodology was assessed by comparison of this approach and a cartographer made set of generalized contour lines of the same chart. The results were analyzed with a confusion matrix. The columns represent the tension indicated by the cartographer and the lines corresponding to the output tension estimated by the algorithm.

Table 3. Confusion matrix for the neural network.

Operador/Neural Net

	0	1	2	3	4	5	6	7	8	9	10	Total
0												
1		13	53									66
2			61		1	1						63
3			5	2								7
4			10			1						11
5			15	1	2	120	3	1	1			143
6								2				2
7												
8												
9												
10												
Total		13	144	3	3	122	3	3	1			292

Pa – 67%

Table 4 - Confusion matrix for the C5 decision tree.

Operator/Decision Tree

	0	1	2	3	4	5	6	7	8	9	10	Total
0												
1			7									7
2		13	128	2	1	36						180
3												
4			2		1	19						22
5			7	1	1	54	2	1				66
6						3	1					4
7						10		2	1			13
8												
9												
10												
Total		13	144	3	3	122	3	3	1			292

Pa – 63%

Table 5 - Confusion matrix for the C&R Tree

Operator/ C&R Tree

	0	1	2	3	4	5	6	7	8	9	10	Total
0												
1			7									7
2		13	129	2	1	36						180
3												
4			2		1	19						22
5			5	1	1	55	2	1				66
6						3	1					4
7						10		2	1			13
8												
9												
10												
Total		13	143	3	3	123	3	3	1	0		292

Pa – 64%

Table 6 - Confusion matrix for the Output after the Agent.

Operador/Agent

	0	1	2	3	4	5	6	7	8	9	10	Total
0												
1		5	1									6
2		8	126	2		15						151
3					1							1
4			6		2	4						12
5			11	1	1	102	3	1	1			120
6												
7								2				2
8												
9												
10												
Total		13	144	3	4	121	3	3	1			292

Pa – 81%

Pa – Percentage of agreement

The biggest tensions are not used nor by the operator nor by the methods of AI, therefore for this ratio of scales the deformation of the line does not have to be high. With the use of the agent it has a substantial profit in the prediction of the value of the tension to use, when we combine the three methods.

6. SELF CORRECTION TO ENSURE CONSISTENCY OF CONTOUR LINES, HEIGHT POINTS AND WATER LINES

The generalized contour lines are also subject to a contextual analysis. We add a control process which ensures that every contour line is analyzed relatively to its neighboring spot heights. If the local topology is changed by the proposed generalization, an alternative solution is tried and the contour line is generalized constrained to the local topology. We have developed a strategy to fine tune the tension parameter used on the generalization constrained to the local topology.

Assuming that a spur exists and the height point is necessary to define it. After the applied tension to the line, the generalized contour line passes beyond the spot height, having here a clear violation of topology, see figure 7.

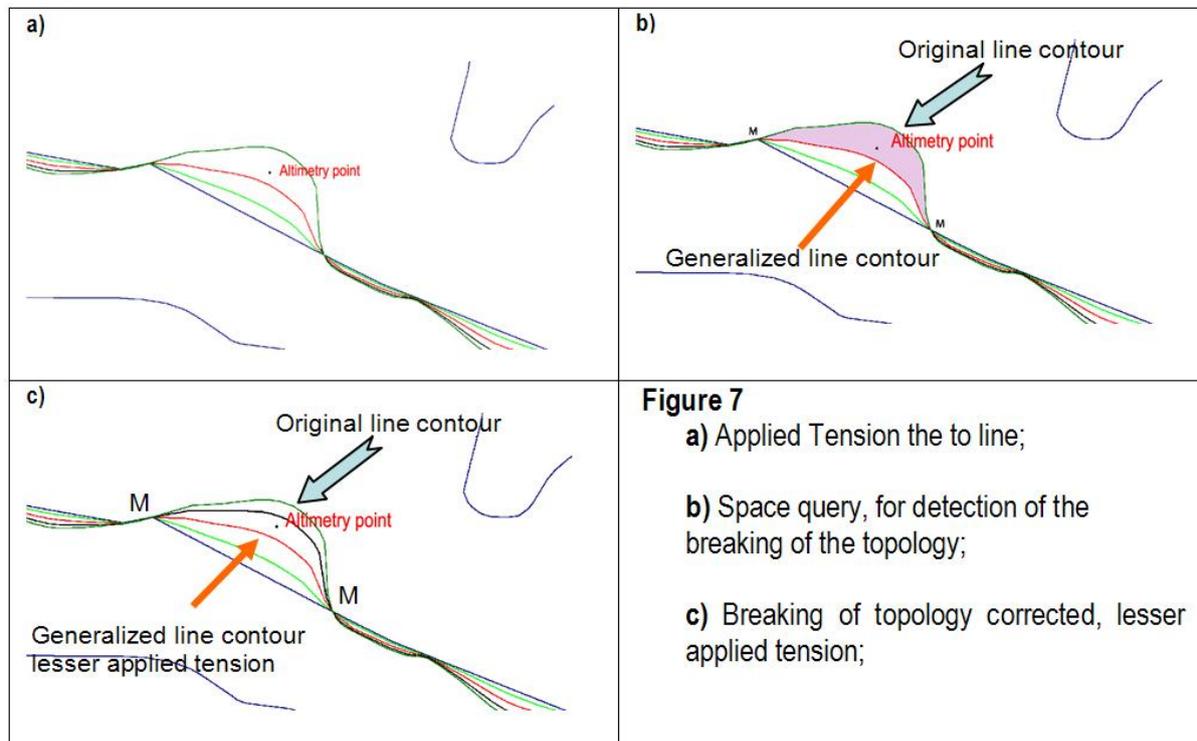


Figure 7
 a) Applied Tension the to line;
 b) Space query, for detection of the breaking of the topology;
 c) Breaking of topology corrected, lesser applied tension;

If the altimetry point will be in the interior of the area defined for the two contour lines, (original and generalized) limited for the average points M_i and M_{i+1} , then we have a problem of violation of topology. In the correction of this problem, it's necessary to apply an inferior tension in this part of the contour line, see figure 7.

Contextual Generalization between Contour lines and Water lines

In the matter of the contour line intercept a water line, between the points M_i and M_{i+1} , so the intersection point will be a local maximum, because of the Brisson Theory “when a contour line crosses a water line it suffers an inflection, turning the convection to the flux” Alves (1984). After the application of the algorithm of generalization, that point could not be the maximum. In this case the algorithm of generalization is adapted to this particular situation, executing the next steps, as we can see in the figure 8:

-1° step: Detect the existence of an interception between the fragment of the contour line and the water line (Max_0);

-2° step: Apply the calculated tension by the presented methodology;

-3° step: Detect the existence of an interception between the fragment of the generalized contour line and the water line (Max_1);

-4° step: Calculate the moving vector

$$\overrightarrow{Max_0 Max_1}, \text{ parallel to vector } \vec{A};$$

5° step: Apply in points of the generalized curve the proportional vector moving to \vec{A} , in the following way, see figure 8:

$$\left\{ \begin{array}{l} displacement_k = \frac{\|M_i P_k\|}{\|M_i Max_p\|} \times \overrightarrow{Max_0 Max_1} \\ displacement_j = \frac{\|P_j M_{i+1}\|}{\|Max_p M_{i+1}\|} \times \overrightarrow{Max_0 Max_1} \end{array} \right.$$

This way the moving of the point its maximum in the crossing point of the contour line with the water line, reducing its value progressively, when we approach M_i , being null in the M_i points .

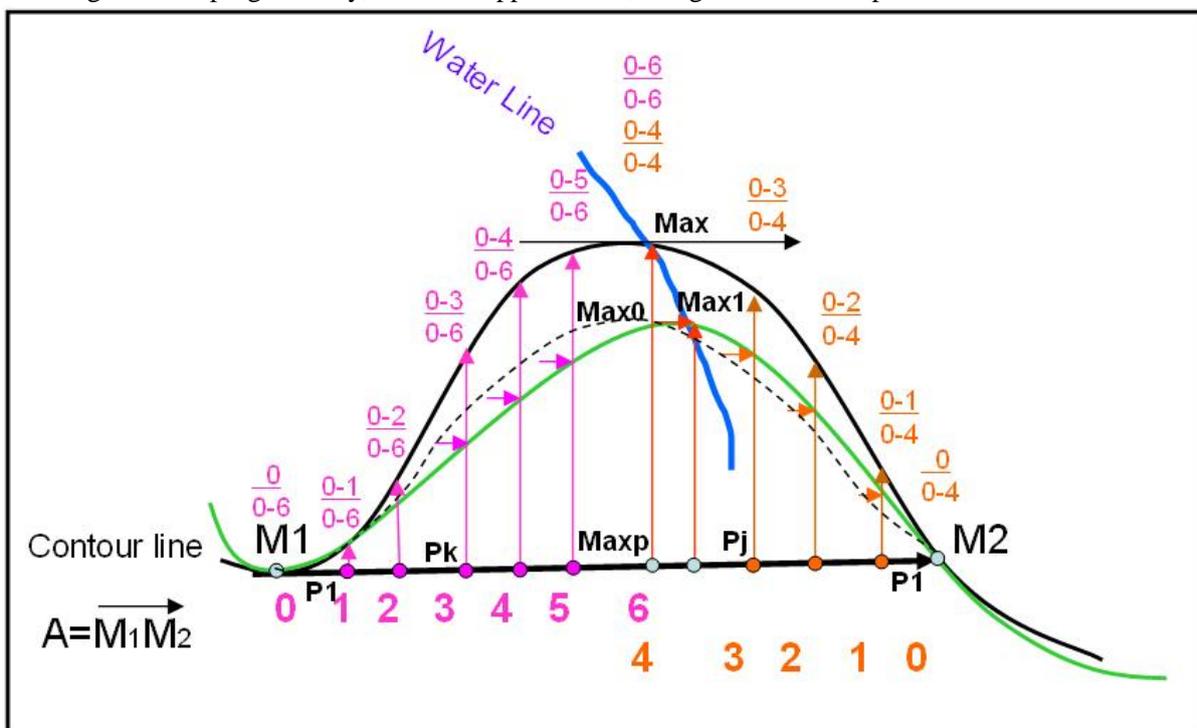


Figure 8 – Contextualization of the generalization of the contour lines with the water lines

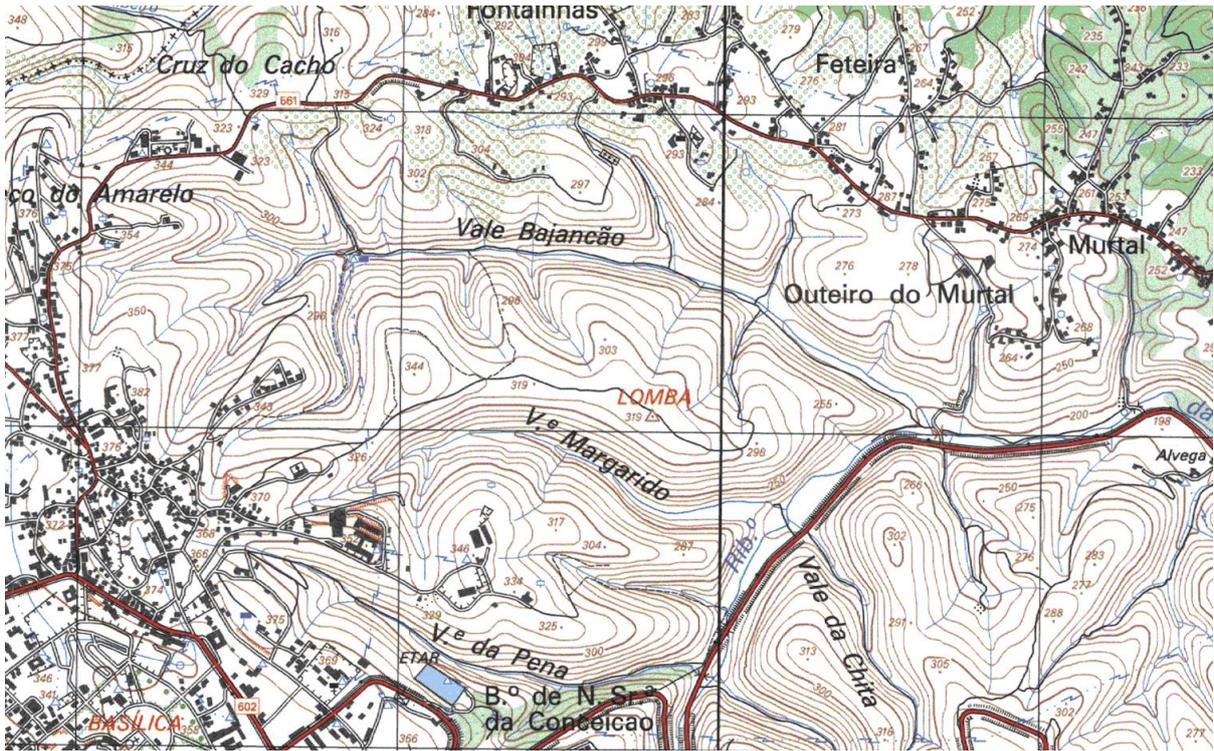
7. VALIDATION AND RESULTS

In order to validate our approach, we submitted a generalized map to cartographers.

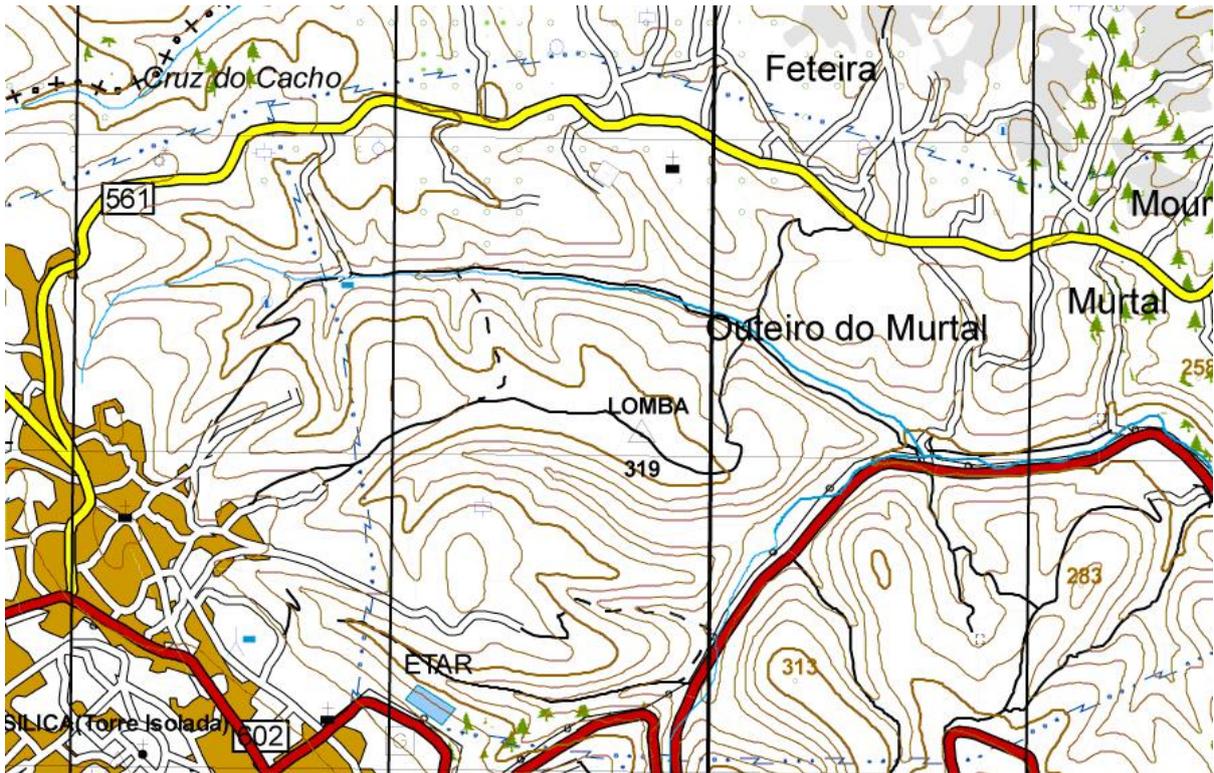
-The time of the operator spent in average per map in manual generalization of contour lines is 35 hours, with this methodology it can be reduced in about 95%.

-The time spent in contextualizing the themes of the contour lines, elevation points and water lines could get in average 8 to 10 hours per map, with this methodology, we can earn about 90% in time.

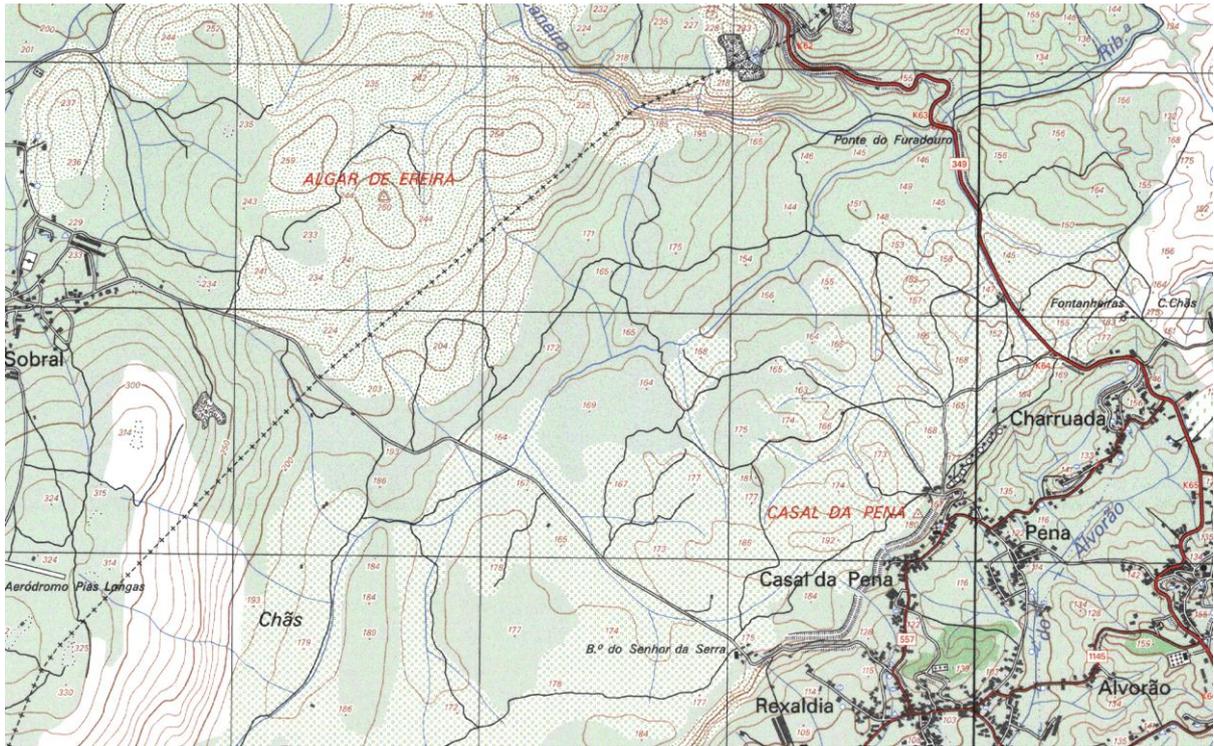
The generalized line contours with the parameters predicted for the techniques previously presented are adjusted for scale 1/50.000, see figure 9.



50K



25K



50K

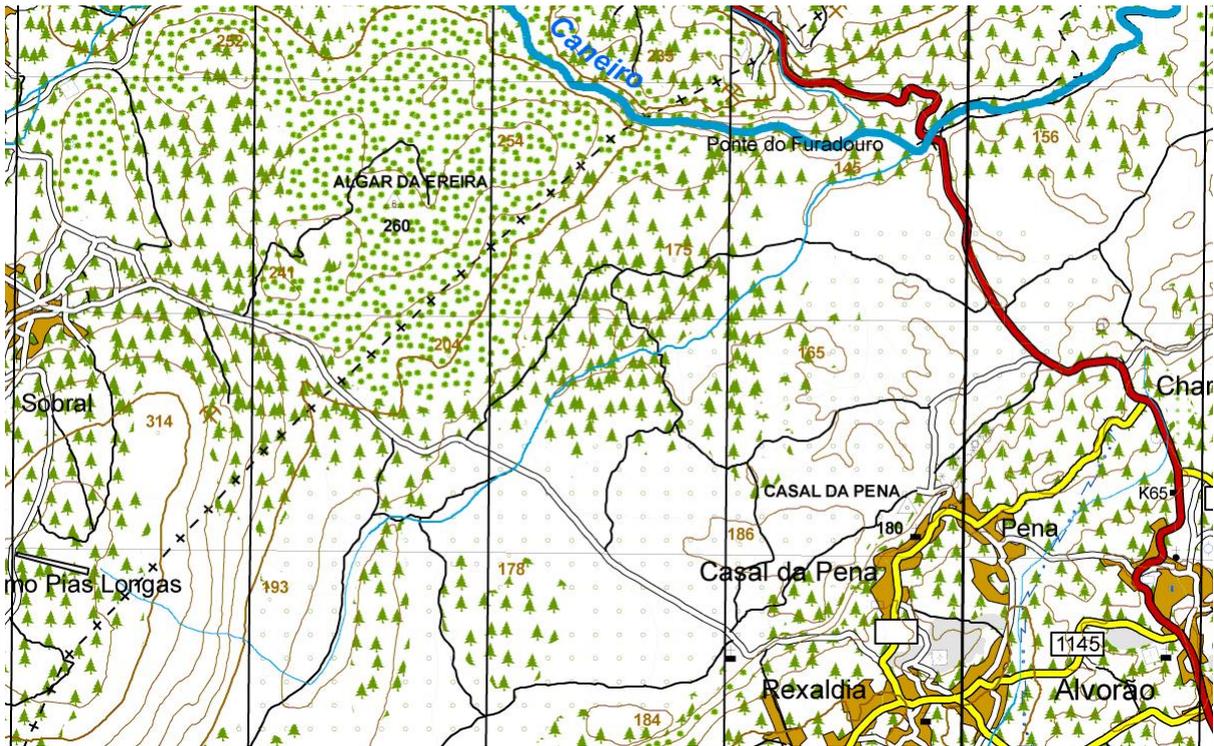


Figure 9 – Source contour lines at scale 1/25k and generalized at scale 1/50k

8 – CONCLUSION

Artificial intelligence is one of the promising technologies to integrate in the search of a solution for the automatic cartographic generalization, however it is still early for being able to integrate all the available technology.

The combination of some methods of AI substantially improves the prediction of the value of the tension to use. The use of other algorithms or sequence of algorithms is also possible with this methodology, we only need to make the class and training the AI techniques.

It's very important that we have in matter strategies to contextualize the generalization and solve the aspects that are beyond the geometric problems.

The outputs of the three methods were analyzed and these results foresee a vast application to other subjects and algorithm chains. The comparison between the automatic generalization performed by the three AI algorithms with a man made generalization agrees within 63% to 67%. When the three solutions are combined with and Agent the quality of the generalized curves are increased to 80%. This is remarkable result considering the level of agreement with man made generalization and the reduced time span (about 35 minutes for a 1/25k map).

Those days, it's more realistic to propose a solution to a specific cartographic problem, since the global and integral solution have many variables and, our map needs are different from case to case.

Thus the proposal presented here is only one drop in the ocean only intending to solve a small problem in the immensity of this process that is the generalization. We must refer that the algorithmic solution may not exist, being always necessary final work of an operator.

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