

Extraction of linear structures from LIDAR images using a machine learning approach

Clément Laplaige¹, Jean-Yves Ramel², Xavier Rodier³ Bechir Ben-Rhima⁴

¹ UMR 7324 CITERES, LAT, rue Watt 37200 Tours, clement.laplaige@univ-tours.fr

² Laboratoire Informatique de Tours, 64 av Portalis 37200 Tours, jean-yves.ramel@univ-tours.fr

³ UMR 7324 CITERES, LAT, rue Watt 37200 Tours, Xavier.rodier@univ-tours.fr

⁴ Laboratoire Informatique de Tours, 64 av Portalis 37200 Tours, bechir.benrhima@gmail.com

For extraction and characterization of archeological structures from LiDAR data, most studies focus on manual spotting (vectorization) or automatic image processing (IP), while few studies have examined semi-automated methods based on machine learning (ML). In the context of the Solidar project, after trying to use classical image processing techniques, we propose to reflect on elements to be integrated in ML approaches for a better and a more flexible extraction and characterization of archeological structures discovered in the LiDAR datasets.

Indeed, the LiDAR data reveal many varied remains over large geographic areas. Manual digitizing of these remains is a time-consuming activity and does not guarantee an exhaustive recognition of features. This article proposes to present: (1) the archaeological context of this work, (2) the searched objects in this study, (3) the first tests and (4) how the data will be processed in the near future.

I. INTRODUCTION

LiDAR technology makes it possible to generate highly accurate elevation models from the ground whatever the nature of the plant cover. Lidar elevation models have multiplied during the past decade, delivering an unprecedented amount of original archaeological finds in the forest. These features correspond to habitat, agricultural or funeral structures before the existence of forest cover but also archaeological micro-structures directly linked to past forest economy.

Beyond the Digital Elevation Model (DEM), data obtained by Lidar surveys provide useful information about the evolution of the countryside. They can thus be an indirect indicator of the consequences of human impact in the long term (from the origins to the present day) on current stands.

For extraction and characterization of archeological structures from LiDAR data, most studies focus on manual spotting or automatic image processing (IP), while few studies have examined semi-automated

methods based on machine learning (ML). In the context of the Solidar project, after describing the archaeological issues of this work and trying to use classical image processing techniques, we propose to investigate machine learning approach for a better and a more flexible extraction of archeological structures from LiDAR derivatives.

II. CONTEXT

A. Study Area and Data Sources

This work is part of SOLiDAR project which is part of the interdisciplinary program of research and innovation “Intelligence des Patrimoines”.

The program is based on LiDAR survey of 270 km² located around the city of Blois (Loir et Cher, France) (fig. 1) including the forests of Blois, Boulogne, Russy and the Chambord estate. The LiDAR acquisition was performed at the beginning of 2015.

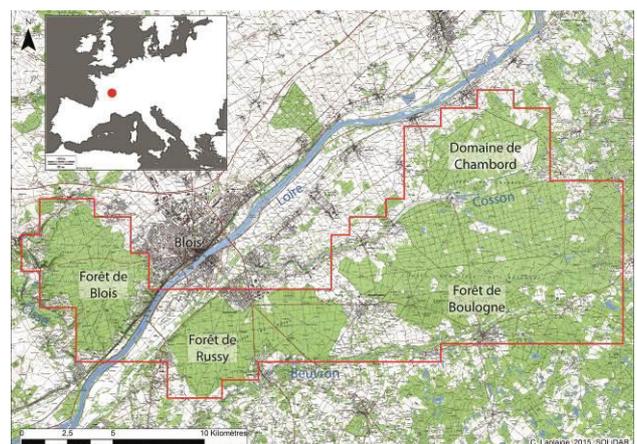


Fig. 1. Location of the acquisition. The red line corresponds to the boundaries of LiDAR

The average density of ground points is about 10 pts / m², which allows us to generate DTM with a resolution of

50 cm.

Analysis of LiDAR data revealed the density of linear elements, largely novel. In total more than 2000 km of lineaments that have been vectorized manually (fig. 2). Manual digitizing of these remains is a time-consuming activity and does not guarantee an exhaustive recognition of features.

Until recently, the LiDAR acquisitions in France were limited to small areas. However, the recent and rapid supply of large-scale reference by the National Geographic Institute is now supplying us lot of data at very high resolution on surfaces of several thousand km² in previously little known areas by an archaeological point of view.

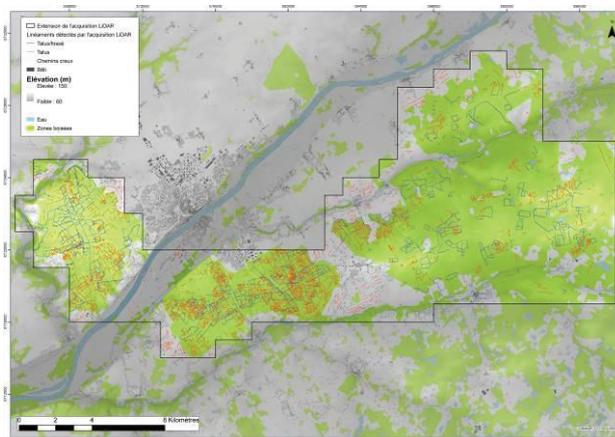


Fig. 2. Linear structures discovered by LiDAR and fieldworking represented in blue and red

B. Related works

There are many methods for automatically process the LiDAR data. The best known methods are pixel analysis [1]. Last decade, following the work of geographers and computer scientists, more efficient methods have emerged like template matching or segmentation [1, 2, 3, 4].

The use of Machine Learning approach [5, 6, 7] has received growing attention because of increasing availability of easy to use libraries and software. Martha et al. [4] used optical images for segmentation and auxiliary elevation data for landslide detection. Anders et al. [8] used LiDAR DEM-derived features for geomorphological change detection. Eisank et al. [9] used DEM data for drumlin delineation. Van den Eeckhaut et al. [10] have used the support vector machine (SVM) algorithm and LiDAR derivatives alone for object-based mapping of landslides in forested terrain.

III. PROBLEM DESCRIPTION

A. Selection of the Elements of Interest

Because visual analysis and manual spotting (vectorization) is a tedious task with a risk of subjectivity and non-exhaustively, we decided to focus our study on specific EOI for archeologists that are linear structures (lineaments).

Indeed, raw LiDAR data analysis showed that there was, in the study area, at least three plots frames overlapping (fig. 3).

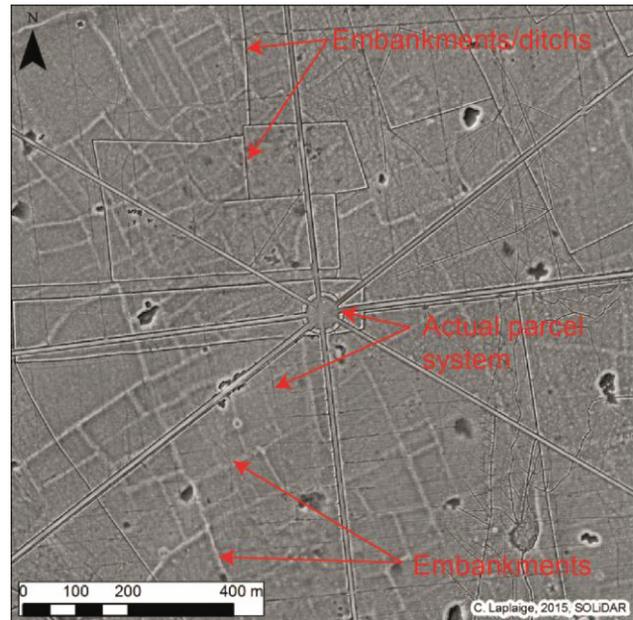


Fig. 3. Different type of linear structures discovered in the LiDAR dataset. The DTM is represented by a Topographic Position Index with a transparency on a hillshade

On the model derived from LiDAR data, we can see in the foreground the current parcel frame system. This frame overlaps a system of embankments and ditches.

This system consists of rectangular, square or polygonal modules, which are embedded or not.

In section, the embankments-ditch structure measures an average of 6 to 8 m wide to a depth less than one meter (fig. 5-1). These elements were identified by fieldwalking before the LiDAR survey.

This system overlaps a system composed uniquely by embankments. These elements are fifteen meters wide for 10-15 cm high (fig. 5-2). This plot system was unknown before the LiDAR acquisition because the human eye is unable to recognize these artefacts on the field. Some of the most impressive elements can be seen in situ only if you specifically looking for them with a handy LiDAR background.

Unlike the embankments-ditch system, which was composed by large polygonal parcels, this system is composed by tiny rectangular shapes.

The obvious overlap between these three parcel frames gives us a beginning of relative chronology. The

embankments system is the oldest, then comes the embankments/ ditches system and finally the current occupation frame.

Finally, the morphological variability between these three systems suggests a different use of the space.

Actually, a system dedicated to hunting and forestry activities, before that, a system used, maybe, for the same purpose and before, an open landscape probably dedicated to agropastoral activities.

According to these discussions between archeologists and computer scientists, we decided to define 5 different categories (classes) of linear structures that seem interesting to study (see figure 4, 5, 6):

- Embankment/ditch (1), which corresponds probably to the previous silvicultural system
- Embankment (2), which corresponds to the former system and turned to agricultural activities.
- Ditch (3), with drainage functions.
- Modern road system (4)
- Probable hollow path (5)

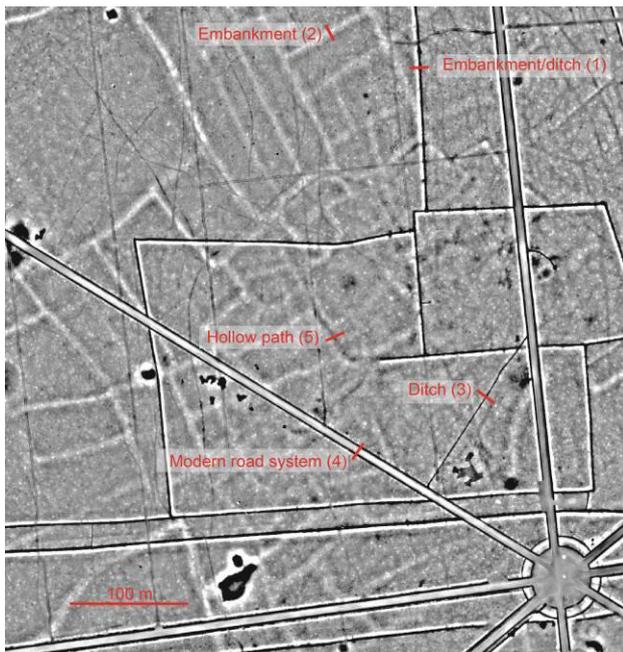


Fig. 4. Classes of interest

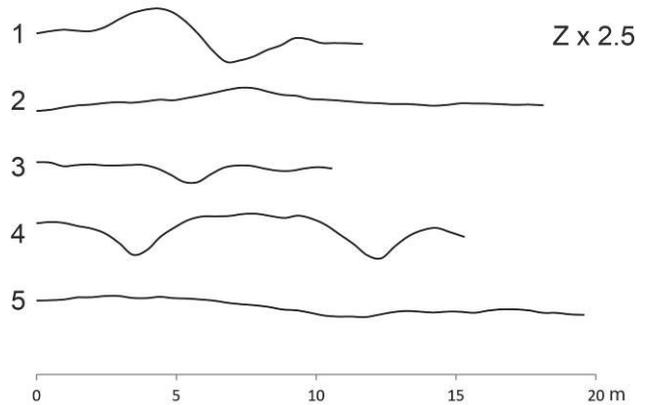


Fig. 5. Micro relief anomaly corresponding to classes of interest. (1) Embankment/ditch, (2) Embankment, (3) Ditch, (4) Modern road system, (5) Hollow path. Vertical exageration = 2.5

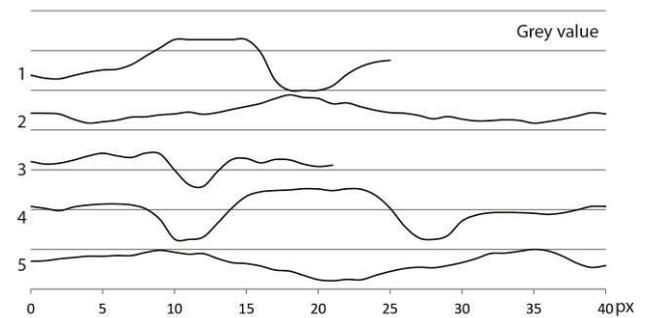


Fig. 6 . Variation of grey value on the Topographic Position Index corresponding to classes of interest. (1) Embankment/ditch, (2) Embankment, (3) Ditch, (4) Modern road system, (5) Hollow path.

The objectives is then to produce a tool (a framework) that allows a semi-automatic detection and characterization of the selected EOI starting with the available DEM computed from the LIDAR data (see Fig. 9). For the selected case study, the output of the system should be 5 layers (binary images) each one giving the position (by black pixels) of the researched elements (EOI). These resulting images can be vectorized to get the final results. For example ditches search results are shown on Figure 7.

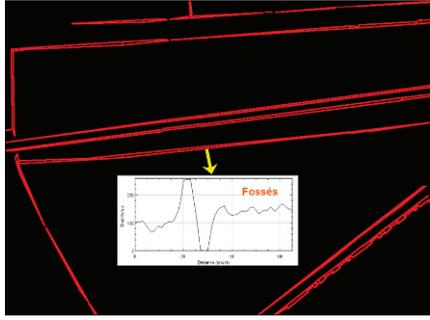


Fig. 7. Example of the desired final results(vectorised linear structures)

B. Problem resolution using Image Processing

As a first approach, we tried to apply classical image processing approach (see fig 9) to try to discriminate the previously defined categories. The goal was the separation of the pixels of an initial image into the 5 targeted information layers. As already explained, one layer should correspond to one binary image that can be vectorized to get the linear structures of a specific category.

Different processing sequences (fig. 8) have been tested including: image filtering (median /Gaussian...), multiple thresholding, mathematical morphology operations, connected component analysis and arithmetic operation between processed DEM and layers.

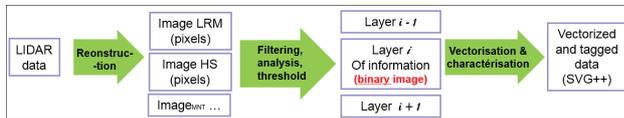


Fig. 8. Image analysis approach



Fig. 9. Illustration of an image processing sequence

The obtained results demonstrate that this kind of approach was very difficult to use to discriminate correctly between the 5 desired categories. Furthermore, in this case, parameters and thresholds setting is a tedious task impossible to reconduct to process different images. It means that the obtained framework will be dedicated only to a very specific task (linear structure detection) on a very limited number of specific images.

C. Problem resolution using Machine Learning

It seems more interesting to define a more flexible and robust framework based on a machine learning approach.

The main idea of such approach is to find a clever way to combine information coming from the DEM (LIDAR data) in order to decide for each pixel if it is part of a specific Element of Interests. Furthermore, the provided decision for each pixel should not be a binary one (yes or no – black or white) but a set of probabilities corresponding to the chance for the pixel to be part of each possible category (class). The output of this new framework will be a set of matrices called “probability maps”. Each probability map includes the probabilities for each pixel of the image to be part of a specific EOI (see fig 10).

Furthermore this tool is built using the linear structure use-case but should be easily adaptable for the detection and recognition of other archeological element of interests (EOI).

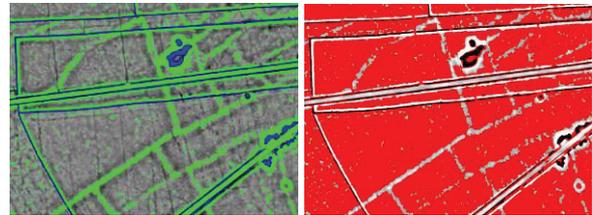


Fig. 10. Example of probability map (1 color corresponds to a probability value for being part of a specific class)

IV. DESCRIPTION OF THE ML FRAMEWORK

The proposed framework is described figure 11. The main concepts used in this framework are described in the following subsections.

Currently, the tool is still in development and we are only able to outline the future functionality of our system

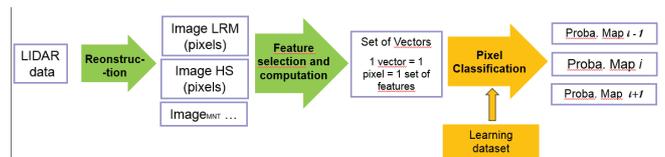


Fig. 11. Framework with a Machine learning approach

When designing a classification system, the selections of the features to describe the pixels as well as the content of the training dataset are extremely vital because they determine the quality of the classification results.

A. Feature definition

The first step is to select the input images (DEM) that will be used to compute the pixel features. Based on the expertise of archeologists and also on the result obtained with IP methods (see section III.A), we have selected, for a first experience, only the Topographic Position Index

proposed by Jeff Jenness with a resolution of 2m to compute the features.

Then, a list of features has been defined based on our experience in computer vision. These features are inspired by the well-known and quite efficient LBP (local binary pattern) method [11] in which a local neighborhood is thresholded according to the gray level value of the central pixel to provide a binary pattern called texture unit. The numbers of occurrences of each texture unit are then used as descriptors of a region inside an image. We propose an adaptation of this idea to compute the features included in our framework by also considering a local neighborhood (of variable size – colored squares in figure 12) around a central pixel (red cross in figure 12). The proposed features are computed using statistics about gray level values in different neighborhoods in addition to gray level values compared to the value of the central pixel. The firsts parameters included are listed in table 1. However, this list will evolve rapidly based on our progress.

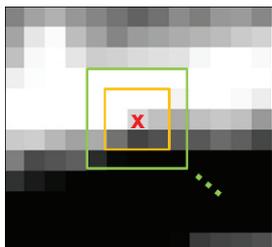


Fig. 12. Local Feature computation

Table 1. Proposed Local features

Feature	Description
I _{x,y}	Intensity of the central pixel
Min3x3	Minimum of the differences between central value and neighboring values in 3x3 mask
Max3x3	Maximum of the differences between central value and neighboring values in 3x3 mask
Avg3x3	Average of the differences between central value and neighboring values in 5x5 mask
Wleft3x3	Number of Fair pixels at the left of the central pixel
Gleft3x3	Number of Gray pixels at the left of the central pixel
Bleft3x3	Number of Dark pixels at the left of the central pixel
Wtop3x3	Number of Fair pixels at the top of the central pixel
Gtop3x3	Number of Gray pixels at the left of the central pixel
Btop3x3	Number of Dark pixels at the top of the central pixel
Wright3x3	Number of Fair pixels at the top of the central pixel
Gright3x3	Number of Gray pixels at the right of the central pixel
Bright3x3	Number of Dark pixels at the right of the central pixel
Wbot3x3	Number of Fair pixels at the bottom of the central pixel
Gbot3x3	Number of Gray pixels at the bottom of the central pixel
Bbot3x3	Number of Dark pixels at the bottom of the central pixel
...	3x3 values can be duplicated for 5x5, ... neighborhoods

Different DEM can also be used to compute more features

Starting from this exhaustive list of features, both subjective and objective methods can be used to select the useful features for a specific classification problem. Subjective methods are often based on past experience and user knowledge, while the utilization of feature selection algorithms is relatively more objective.

In a first attempt, our software will let the user (expert) select in a subjective way, the adequate features to extract for a specific type of EOI (linear structure in our first case study). For the moment, no automatic feature selection method is applied to pick useful features objectively but this kind of algorithm could be plugged into the system later. In a same way, geometric and contextual semantic features were not used in this study, and could be considered in the future.

B. Classification model definition

In order to have a generic framework, we will develop a specific module in our software dedicated to the construction of a Learning Set (LS) needed by the classifier. As we want to classify pixels, the LS correspond to a huge table (matrix) containing a large number of feature vectors representative of each the pre-defined classes. A specific module of the software has been developed to simplify the creation of this table (LS) starting from some representative initial images (Topographic Position Index) for which the ground-truth (labels of classes) have been provided by archeologists, as set of binary images that indicate some positions of examples of desired EOI to learn. The user (of our software) “just” has to create a specific directory for each class of EOI he want to extract and put inside each of these directories some couple of initial images plus corresponding binary images showing good examples of the EOI to learn. Then, the software will parse all the directories and create the corresponding learning set.

For the classification, different machine learning algorithms can be adopted and plugged into our framework. For the moment, we incorporate a SVM classifier inside the system. SVM is a non-parametric kernel-based technique based on statistical learning theory, optimization algorithms, and structural risk minimization theory [12], and it has been used in many studies [10,13]. SVM parameter optimization can be done using a N-fold cross-validation grid search function. In this study, a radial basis function kernel was used, and the cost and gamma parameters had to be optimized empirically.

C. Post-Processing

After the classification, probability maps corresponding to all the desired classes of Elements of Interest have to be combined to provide the final decision. Different fusion techniques can be used during this step. In this first study, we use a maximum rule with reject option for the combination and each pixel is affected to the class having the maximum probability only if the value is higher than a predefined threshold chosen empirically. Then, the obtained binary image can be vectorized in a similar way as binary images obtained with a classical image processing sequence (figure 7). We use the vectorization algorithm described in [14] for that purpose.

V. CONCLUSION AND PERSPECTIVES

This work is a first attempt to develop a generic Machine Learning framework for the semi-automatic extraction of archeological Elements based on LiDAR DEM.

We are at the beginning of the work and have focused on the extraction of linear structures (lineaments). However, the first tests quickly revealed the interest of the Machine Learning approach compared to image processing techniques.

We hope to quickly obtain a flexible system capable to objectively extract but also characterize different types of searched objects under some geomorphological conditions.

Furthermore, the generation of probabilities rather than binary images as results of the extraction will probably allow the creation of new databases that we can interpret as well.

URL

SOLiDAR program :
<http://citeres.univ-tours.fr/spip.php?article2133>

Intelligence des patrimoines :
<https://www.intelligence-des-patrimoines.fr>

Topographic Position Index :
<http://www.jennessent.com>

REFERENCES

- [1] Sevara C., Pregebauer M., Doneus M., Verhoeven G., Trinks I., "Pixel versus object — A comparison of strategies for the semi-automated mapping of archaeological features using airborne laser scanning data", JAS : Report 5, 2016
- [2] Baatz, M., Hoffmann, C., Willhauck, G., 2008. Progressing From Object-based to Object-oriented Image Analysis. Springer, Heidelberg.
- [3] Blaschke, T., "Object based image analysis for remote sensing". ISPRS J. Photogramm Remote Sens., 2010, 65 (1), 2–16.
- [4] Martha, T.R.; Kerle, N.; Jetten, V.; van Westen, C.J.; Kumar, K.V. Characterising spectral, spatial and morphometric properties of landslides for semi-automatic detection using object-oriented methods. *Geomorphology* 2010, 116, 24–36.
- [5] Xianju Li, Xinwen Cheng, Weitao Chen, Gang Chen and Shengwei Liu, "Identification of Forested Landslides Using LiDAR Data, Object-based Image Analysis, and Machine Learning Algorithms", *Remote Sensing*, 2015, 7, 9705-9726.
- [6] Chen, W.; Li, X.; Wang, Y.; Chen, G.; Liu, S. Forested landslide detection using LiDAR data and the random forest algorithm: A case study of the Three Gorges, China. *Remote Sens. Environ.* 2014, 152, 291–301.
- [7] Duro, D.C.; Franklin, S.E.; Dube, M.G. A comparison of pixel-based and object-based image analysis with selected machine learning algorithms for the classification of agricultural landscapes using SPOT-5 HRG imagery. *Remote Sens. Environ.* 2012, 118, 259–272.
- [8] Anders, N.S.; Seijmonsbergen, A.C.; Bouten, W. Geomorphological change detection using object-based feature extraction from multi-temporal LiDAR data. *IEEE Geosci. Remote Sens. Lett.* 2013, 10, 1587–1591.
- [9] Eisank, C.; Smith, M.; Hillier, J. Assessment of multiresolution segmentation for delimiting drumlins in digital elevation models. *Geomorphology* 2014, 214, 452–464.)
- [10] Van den Eeckhaut, M.; Kerle, N.; Poesen, J.; Hervas, J. Object-oriented identification of forested landslides with derivatives of single pulse LiDAR data. *Geomorphology* 2012, 173, 30–42.
- [11] T. Ojala, M. Pietikainen, and D. Harwood. A comparative study of texture measures with classification based on feature distributions. *Pattern Recognition*, 29(1) :51–59, 1996. 1, 3, 4
- [12] Vapnik, V. *The Nature of Statistical Learning Theory*; Springer-Verlag, Inc.: New York, NY, USA, 1995.
- [13] Peng, L.; Niu, R.; Huang, B.; Wu, X.; Zhao, Y.; Ye, R. Landslide susceptibility mapping based on rough set theory and support vector machines: A case of the Three Gorges area, China. *Geomorphology* 2014, 204, 287–301.
- [14] Ramel J.-Y., Vincent N., Emptoz H., "A structural representation for understanding line-drawing images.", *IJDAR* 3(2): 58-66 (2000)