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Automatic interpretation of scanned maps : Reconstruction of contour lines

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This paper deals with the problem of automatic reconstruction of contour lines out of scanned maps. Our approach is essentially based on the global topology of the contour lines (ie. a set of non-intersecting closed lines), but we use also some local and geometrical informations to guide the reasoning.

Our proposed method starts from a map scanned in RGB. The image is first segmented by a colour classification process, and the objects are skeletonized end vectorized. Then, by a local analysis, we weight and add some hypothetical edges. By a relaxation process, we try to orientate the elevation curves, and so we could re-adjust the weight. Finally, we found a topologycally correct solution by resolving the dual problem (ie. a bicolouring problem).

1 Introduction

The problem of automatic interpretation of scanned maps gives rise to a lot of research efforts at different levels : Classification of colours ([1] and [4]), extraction and reconstruction of lines, symbols and characters ([11], [5] and [3]), reconstruction of road and hydrographic networks ([12] and [13]). Those kinds of studies are aiming to create Geographical Information Data Base.

Here, we tackle problem of reconstruction of contour lines. Because of the density and the topology of these curves, the interpretation of the contour lines, in the way to create a Digital Terrain Model, is a very hard and expensive process, even for a human operator.

Previous studies have shown that the geometry of lines does not provide sufficient evidence for an automatic reconstruction of closed height contours. To bypass this insufficiency, most of the related papers describe systems involving the intervention of an operator. In this kind of technique, the role of the operator is to resolve the ambiguities induced by interruptions or multiple connections of curves and/or to correct the result ([9] and [2]). The principal problem of this approach is that the number of interactions is often very high. To reduce this number, Goodson in [7] proposes to use a knowledge based system. This semi-automatic system attempt to resolve the difficulty by consulting a knowledge data-base, and the operator will be consulted only if the system can't resolve the ambiguity by itself. The knowledge which the operator uses to resolve the ambiguity should then be represented in the data base.

We can also cite the agent-based parallel method developed by Shimada *and al* in [14]. Shimada introduces a vector trace agents, and propose a cooperative negotiable environment between agents to pass through irregular part of contour lines. Here, the role of the operator is to initialize the agents.

For a completely automatic method, we must consider the problem as a global problem. An approach is to use external information. For example, Yamamoto proposes in [8] to use the quotations points. With this information, he construct a relief by minimizing a global energy function. But this kind of approach failed in case where external information is too sparse.

Our approach is basically rely on the contour lines' topology. The reconstruction is based on a global bi-coloring process ([10]), that is trying to construct a topologycally correct relief with two altitudes (Black and White). This relief must fit as well as possible with the contour lines present on the map. But, when some curves are broken, many differents topologically correct reliefs can be created. In our method, we try to guide the reconstruction process by the use of *a priori* knowledges and by the computation of the orientation of the contour lines.

2 Pre-treatment

The input images are scanned in RGB (Red-Green-Blue) at 500 dpi directly from the paper maps. We compute a label image containing, for each pixel, a number corresponding to one of the pure colour presents on the map. This classification process is a kind of watershed divide on the RGB histogram. Then we regroup those labels into four classes : **(1)** The **Foreground** or **Gray** class corresponding to the colours of the objects that may interrupt the contour lines, **(2)** The **Contour Line** or **Black** class corresponding to the colour of the contour lines, **(3)** The **Background** class corresponding to all the other colours, **(4)** The **Dual of Contour Line** or **White** class corresponding to the union of the Foreground and the Background classes.

We compute two binary images, one for the Black class (Contour Line), and one for the Gray class (Foreground). Then, by a polygonal approximation, we vectorize : **(1)** The skeleton of the Contour Line's binary image, **(2)** The skeleton of the Contour Line's dual binary image, **(3)** The contours of all the objects present on the Foreground binary image.

So we obtain a graph G_r, and three planar sub-graphs : G_{rb}, which contains the black items, G_{rw}, which contains the white items and G_{rg}, which contains the gray items. See figure 1 for an example of pre-treatment.

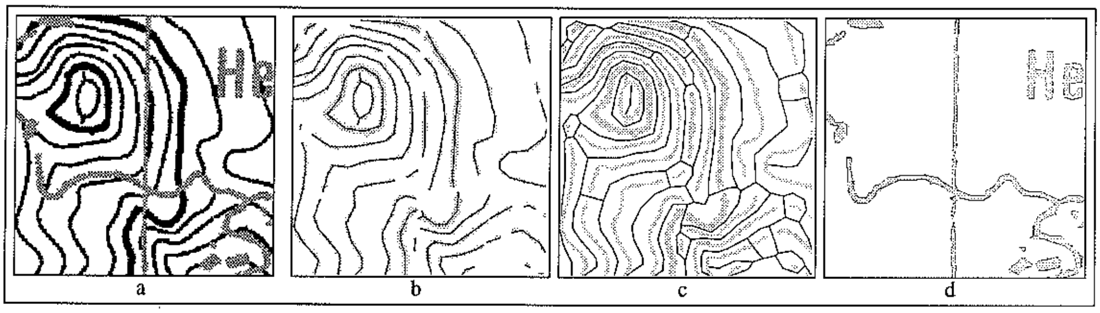

Figure 1: Pre-treatment. (a): Label image (the contour lines are in black, and the foreground objects in gray), (b): G_{rb}, (c): G_{rw}, (d): G_{rg}.

3 Treatment

We apply three kinds of treatments. First we weight and add some hypothetical edges, then we try to orientate the curves and to re-adjust the weight, and finally, we reconstruct the contour lines by a global reasoning.

3.1 Suppression and initial weighting of edges

This process is based on the detection of false portions of curves. False contour lines are often due to a noisy document (see 3.a) or a colour segmentation error. Now define what we call a portion of curve :

Definition 1 (Portion of curve) *Let s be a vertex, $\mathcal{V}(s)$ is the set of all the neighbours of s, and $\mathcal{O}(s)$ is the order of s (ie. $\mathcal{V}(s)$'s cardinal). A portion of curve B_r^j is a set of vertices $\{s_0^j, s_1^j, ..., s_{kj}^j\}$, with : (1) $k^j \geq 2$; (2) $\forall i \in [0..k^j - 1], s_{i+1}^j \in \mathcal{V}(s_i^j)$; (3) $\forall i \in [1..k^j - 1], \mathcal{O}(s_i^j) = 2$; (4) $(\mathcal{O}(s_0) \neq 2$and $\mathcal{O}(s_k^j) \neq 2)$ or $(s_0^j = s_k^j)$.*

Let $l(B_r^j)$ be the length of B_r^j (ie. the number of vertices). We assume that B_r^j is a false curve if $l(B_r^j) \leq 3$. We have developed four rules to detect and suppress false curves. Here, we present a simplified version of those rules. Among other, we have omiting the side effects and the treatment of particular cases.

Rule 1 *In the configuration of figure 2.a, we suppress the portion of curve B_r^0 iff the following conditions are true : (1) $l(B_r^0) \leq 3$, (2) $\mathcal{O}(s_0^0) = 3$ and $\mathcal{O}(s_{k0}^0) = 1$, where s_0^0 and s_{k0}^0 are respectively the first and the last vertices of B_r^0, (3) $l(B_r^1) \geq l_{min}$ and $l(B_r^2) \geq l_{min}$, where l_{min} is a given threshold, (4) There is no black or gray objets into the solid angle define by s_{k0}^0, the orientation of $\overrightarrow{s_{k0-1}^0 s_{k0}^0}$, and the two thresholds d_{max} and ω.*

Rule 2 *In the configuration of figure 2.b, we suppress the portion of curve B_r^0 iff the following conditions are true : (1) $l(B_r^0) \leq 3$, (2) $\mathcal{O}(s_0^0) = 3$ and $\mathcal{O}(s_{k0}^0) = 1$, where s_0^0 and s_{k0}^0 are respectively the first and the last vertices of B_r^0, (3) $l(B_r^1) \geq l_{min}$ and $l(B_r^2) \geq l'_{min}$, where l'_{min} is a given threshold and $l'_{min} > l_{min}$.*

Rule 3 *In the configuration of figure 2.c, we suppress the portion of curve B_r^0 iff the following conditions are true : (1) $l(B_r^0) \leq 3$, (2) $\mathcal{O}(s_0^0) \geq 3$ and $\mathcal{O}(s_{k0}^0) \geq 3$, where s_0^0 and s_{k0}^0 are respectively the first and the last vertices of B_r^0, (3) $l(B_r^{11}) \geq l_{min}$, $l(B_r^{12}) \geq l_{min}$, $l(B_r^{21}) \geq l_{min}$ and $l(B_r^{22}) \geq l_{min}$, where l_{min} is a given threshold, (4) There is only one black edge between the two white vertices s'_1 and s'_2, (5) $|\widehat{\overrightarrow{v'_1 s'_1} \overrightarrow{s'_2 v'_2}}| \leq \alpha_{max}$, where α_{max} is a given angular threshold.*

Rule 4 *In the configuration of figure 2.d, we suppress the portion of curve B_r^0 iff the following conditions are true : (1) $l(B_r^0) \leq 3$, (2) $\mathcal{O}(s_0^0) = 3$, where s_0^0 is the first vertex of B_r^0, (3) $l(B_r^1) \geq l_{min}$ and $l(B_r^2) \geq l_{min}$, where l_{min} is a given threshold, (4) $|\widehat{s_1^1 s_0^0 s_1^2}| \leq \alpha_{max}$, where α_{max} is a given angular threshold, and where s_0^0 and s_{k0}^0 are the second vertices of respectively B_r^1 and B_r^2.*

We apply on all the black sub-graph successively the rules 1, 2, 3 and 4. If it stills in G_{rb} too much vertices with an order greater than 2, we decrease the thresholds and we apply one (and only one) time again the rules 2, 3 and 4. Figure 3.b presents an example of suppression. All the suppressed edges are memorized in a list $\mathcal{L}_{suppr}$.

Then, we weight all the edges of G_{rb} by affecting a value $w(a_i) = d(a_i)$, with $d(a_i)$ the euclidean distance between the two extremities of a_i.

3.2 Adding some hypothetical edges

The goal of this step is to try to reconnect extremities of portions of curves. So we have developed three strategies of reconnection.

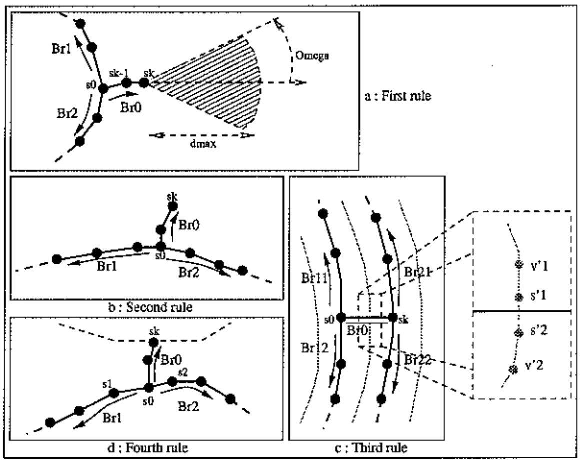

Figure 2: Rules for suppression of false curves. In black : G_{rb}, in gray : G_{rw}

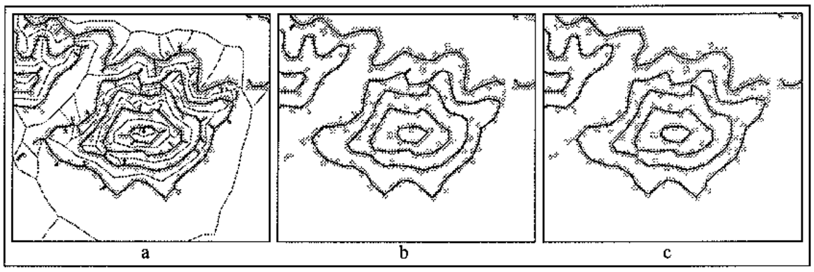

Figure 3: Suppression of false curves. (a): Initial contour lines, (b): Contour lines after one application of the suppression's rules, (c): Contour lines after two applications of the suppression's rules.

The first strategy is based on the analysis of all the foreground's objets. Let O be a gray object, and L be the set of all the extremities s_0^i of portions of curves close to O. Let n be the cardinal of L. To simplify the problem, assume that we have : $\forall i \in [0..n-1], \mathcal{O}(s_0^i) = 1$. So let s_1^i be the unique neighbour of s_0^i. An illustration is given figure 4.a. Then we try to find a set L' of no-crossing edges between the vertices of L, by minimizing an energy function. This Energy function is a sum of quadratic curvatures. An example is given figure 4.c.

Because some interruptions are not due to the foreground's objets, we have adopted two others strategies. So, our second strategy is based on the analysis of the contour lines' dual skeleton. It's an efficient way to resolve the short interruptions. Consult [6] for more details about this kind of analysis. Our third strategy is more efficient for the long interruptions. We estimate the route of a broken curves by following the routes of the parallel curves. It's a sequential version of the Shimada *and al*'s method ([14]). The notion of parallel curves is done by the analysis of the contour lines' dual skeleton (see [6] one time again).

All the edges found after those treatments are not physically added to the sub-graph G_{rb}, but there are memorized in a list $\mathcal{L}_{hyp}$.

3.3 Computation of the orientation

Here we try to orientate the portions of contour lines. To do it, we assume that **(1)** Two parallel curves have rather the same orientation and that **(2)** Two curves which could be connect amongst themselves by an hypothetical edge of $\mathcal{L}_{hyp}$ have rather the same orientation.

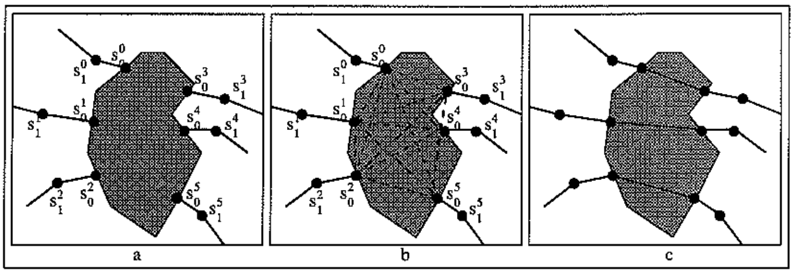

Figure 4: Illustration of the first strategy. (a): Initial configuration, (b): All the possible edges, (c): Selected edges.

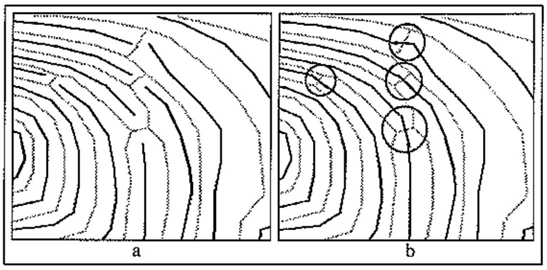

Figure 5: Illustration of the second strategy. (a): Initial configuration, (b): Added edges

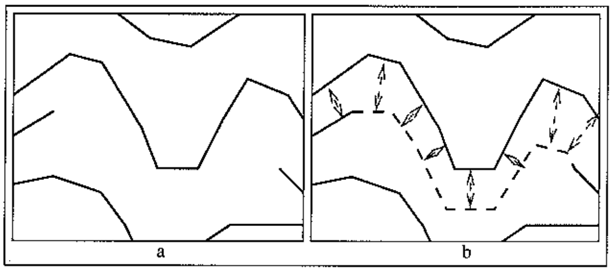

Figure 6: Illustration of the third strategy. (a): Initial configuration, (b): Added edges

Moreover, in the case of a vertex with an order n greater than 2, we select, by applying a minimum curvature criterion, two of the n connected portions of curves. We assume that these two portions of curves have rather the same orientation.

So we define two kinds of neighbourhood relations : **(1)** The parallel neighbourhood relation and the **(2)** The "hypothetical connected" neighbourhood relation.

The first relation is calculated by the analysis of the white skeleton : For all the white portions of curves, we search the two closest black portions of curves, one on the left and the other on the right, and we assume that these two black portions of curves have rather the same orientation. The belief on this relation is proportional to the white portion of curves' length.

The second relation is defined by the edges of $\mathcal{L}_{hyp}$ and the search of vertices of order greater than two. The belief of this king of relation is proportional to the curvature.

To find the best orientation, we use a classical probabilistic relaxation algorithm. Two results are given figure 7.

After having oriented the black curves, we add in the sub-graph G_{rb} all the edges of $\mathcal{L}_{hyp}$. The weight of those edges is $w(a_i) = \frac{1}{2} * d(a_i)$ if the edge a_i is compatible with the orientation, or $w(a_i) = -\frac{1}{2} * d(a_i)$ else.

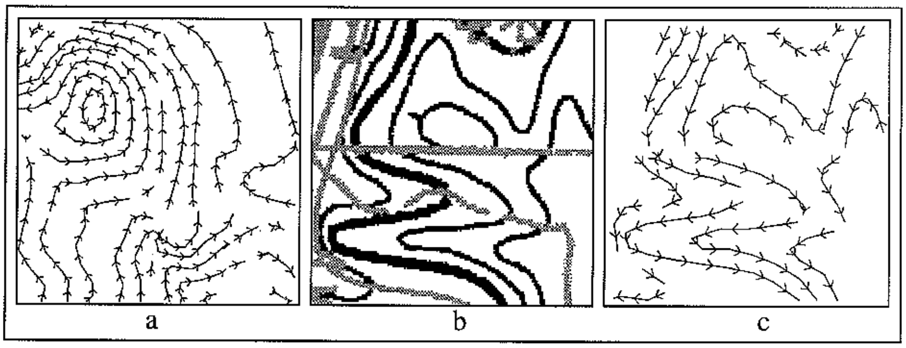

Figure 7: Computing of the orientation. (a): Result for the example of figure 1, (b): An initial image, (c): Result for (b).

3.4 Reconstruction

To be sure to be able to reconstruct the elevation curves, we add in the sub-graph G_{rb} all the possible edges: First, we add the edges of the list $\mathcal{L}_{suppr}$, with a weight $w(a_i) = -\frac{3}{2} * d(a_i)$. Then, we add all the other possible edges by a constraint Delaunay triangulation. The weight of those edges is $w(a_i) = -\frac{1}{2} * d(a_i)$ if the edge connects two extremities of portion of black curves and if it is compatible with the orientation, or $w(a_i) = -\frac{3}{2} * d(a_i)$ else.

Now this is what we call a topological acceptable solution :

Definition 2 (Topological acceptable solution) *A **topological acceptable solution** is a set of disconnected cycles.*

To simplify the reconstruction, we introduce an other definition (the reason is given below):

Definition 3 (Pseudo-topological acceptable solution) *A **pseudo-topologically acceptable solution** is a set of cycles, disconnected by edges.*

Now, we introduce the notion of the weight of a solution. This definition permits us to formalize the problem of reconstruction as an optimization problem.

Definition 4 (Weight of a solution) *Let S be a solution. Let $\mathcal{A}(S)$ be the set of all the edges of S. The weight W of the solution S is $W(S) = \sum_{a_i \in \mathcal{A}(S)} w(a_i)$.*

The formalization of the problem of reconstruction is to find a pseudo-topological acceptable solution that maximize the weight $W(S)$. This is a very hard problem to solve because of the global constraint. But now consider the dual graph G^d_{rb} of G_{rb}. That's mean that all the vertices of G^d_{rb} are the face of G_{rb}, and that there is an edge between two vertices of G^d_{rb} iff the corresponding face of G_{rb} are adjacent. There exist a bi-univoque relation between the edges of G_{rb} and the edges of G^d_{rb}. We also define the weight w^d of an edge a^d_i of G^d_{rb} to be $w(a_i)$.

A bi-coloring Col of G^d_{rb} is an application from the vertices of G^d_{rb} to the set $\{black, white\}$. We define $\mathcal{A}^d(Col)$ to be a set of edges $a^d = (f_1, f_2)$ so that $Col(f_1) \neq Col(f_2)$. We define the weight of a bi-coloring Col to be : $W^d(Col) = \sum_{a^d \in \mathcal{A}^d(Col)} w^d(a^d_i)$.

We have the following result : A solution is a pseudo-topological acceptable solution iff we can bi-colouring the dual graph. The reciprocal is true.

So we have a new formulation of the problem of reconstruction : Find a bi-coloring Col that maximize the weight $W^d(Col)$. We resolve this optimization problem with a probabilistic relaxation algorithm. Consult [10] for more details. An example of bi-colored dual graph is shown figure 8.

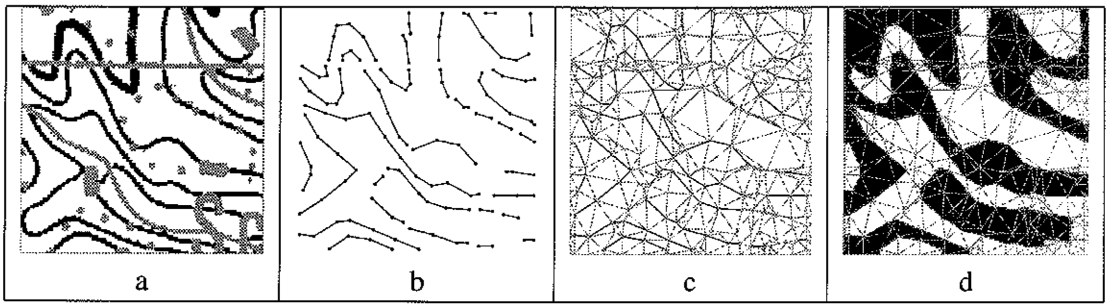

Figure 8: Bi-colouring. (a): Initial image, (b): The black sub-graph, (c): The added edges and (d): The bi-colouried dual graph

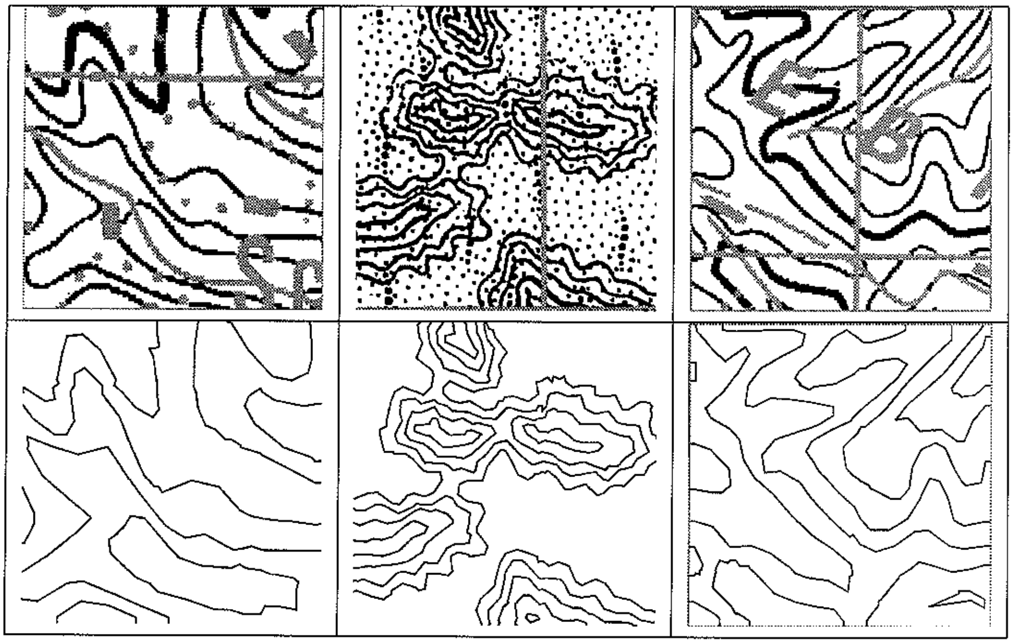

Figure 9: Results. Top: Initial images; Bottom: Result of the reconstruction

4 Post-treatment

To convert the pseudo-acceptable solution into an acceptable solution, and to detect and correct some error of reconstruction, we have developed a global method.

First, we start from the bi-colouried dual graph G^d_{rb} and we colour it with four colours. Then, by analysing the transition of the colours, we are able to detect and correct some error.

5 Results and conclusion

Figure 9 shown some results. To improve these performances, further developments could concern **(1)** The recognition of curves quotations, **(2)** A clusterization of the map (for example by reconstructing in a first stage the master contour lines), **(3)** The use of external data, like the quotations points or a DTM calculated by correlation on satellite images and **(4)** The implementation of a throw back strategy.

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