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A NEW APPROACH TO CREST LINES DETECTION IN GREY LEVEL IMAGES

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ABSTRACT

We aim in this paper to propose a new process for extreme lines detection based on the pretopological model. We set two new algorithms to analyze images of lines (images of the third type). They partly use the principle of functioning of clustering algorithms proposed by H. Emptoz in his thesis (1983), but have a different "philosophy" to interpret the results.

Key words : crest lines, image analysis, pretopology.

INTRODUCTION

Detection of crest lines and valleys in grey level images is actually the subject of an expanding research due to an increase of possible applications. These lines are crucial in analysis of satellite and aerial images (detection of roads, recognition of geomorphological forms,...) and of line images (identification of fingerprints, localization of defaults in composite materials,...). We will name these images "***images of the 3rd type***". In this kind of images the essential information is concentrated in lines of high and low light intensity that we will name "***extreme lines***" (lines of crest or valleys); for detecting them we assimilate the grey level images to a mountainous relief in which we identify tops, crests, valleys... This approach is legitimate because a grey level image can always be represented by parameter surfaces (Marr, 1982).
In the following, we'll briefly describe how the extreme line notion can be apprehended. After that, we'll present the two methods we have developped, and the results they provide on two types of images : images of the BMC (it is the composite material processed by injection), and images taken on cloth samples at the exit of a cloth-drier.

EXTREME LINES

In extreme lines detection the grey level image is often assimilated to a surface in a 3D discrete space. The image is then considered as a mountainous relief. In most of the approaches undertaken to study this relief, the extreme lines notion is apprehended by a ***qualitative description***, i.e. a sort of "definition a priori", doubled by a ***quantitative characterization*** that constitutes a kind of modelization or "formalization"; this characterization is then a "guide" for development of the algorithm realizing the detection. The large variety of these descriptions and characterisations is explained by the diversity of images to be treated, that induces variation of the problems resolution within the type of these images.

Several terms exist to describe a mountainous relief elevated or low : crest, valley, ridge, line of crests, top... We can find there description in a dictionary. For the treatment of grey level images, these definitions were used that way or adapted to the given problem; they are often strongly connected to the method or algorithm that uses them.

Among the characterizations suggested for crest lines and valleys in the literature, we find :
→ "***purely mathematical***" approaches, which use the notion of directional derivative to characterize extreme lines (Haralick, 1983), or the notion of surface curvature in differential geometry;
→ "***signal processing***" approaches, which modelize the profile of an extreme line by a function f which acts as a filter and must supply a significant response in each crest or valley point (Canny, 1983; Ziou, 1991);
→ "***heuristic***" approaches, which are based on a set of criterion that crest or valley points must verify (Salari and al.,1984);
→ "***naturalist***" approaches, which analyze the objects with a naturalist look (Kim, 1985); for example S. Riazanoff and al. (1987) define a crest line (or valley) in an image with grey levels as a path to cover from a select point, with respecting an advance constrain.

NEW APPROACHES FOR CREST LINES DETECTION

This section deals with the presentation of our methods which permit the analysis of third type images. Our approaches are based on the pretopological model. Therefore we need to remind briefly this mathematical tool and then define the pretopology we have use for the realization of our algorithms.

Mathematical tool - Pretopology

A weakling of the axiomatic defining topology led researchers like E. Chech (1966) and other to develop the notion of pretopological structure. It was taken up and extended by G. Duru (1980) to study and analyse the pertinent structures met, in particular, in economic, social, physical or biological sciences. Then it was used in the domain of pattern recognition where it allowed H. Emptoz to modelize the notion of proximity, giving a sense to expressions like "the element x is a neighbour of the element y in E" and/or "the element x is neighbour of the part A in E", and on the other hand to formalize and implement some new methods of clustering. At last, pretopological structures brought their mathematical contribution to the imagery domain for which they represent a tool leading up to computer processing in total agreement with the projected theoretical concepts (Lamure, 1987).
As a matter of fact, pretopology provides non idempotent operators, which allow non iterative algorithms implementation.. This characteristic is interesting because it permits to follow step by step the construction process of the objects belonging to the structure to be detected. We have built two new algorithms for crest lines detection which use pretopological structures.

Notations

* E : support set of a grey level image; and $\mathcal{P}(E)$: set of the parts of E.
* f : grey function of the image, defined by $f : E \to [0 \cdots 255]$ (grey levels scale);
* $V_8(.)$: set of 8-neighbours

General definition

We call *pretopology* on E any function ad_E from $\mathcal{P}(E)$ to $\mathcal{P}(E)$, named *adherence*, and verifies:

(1) $$ad_E(\varnothing) = \varnothing \qquad (1)$$

(2) $\forall A \in \mathcal{P}(E), A \subset ad_E(A);$ (2)

the pair (E, ad_E) is called a *pretopological space* (Duru, 1980).

Now we are going to present our algorithm in accordance with the above rule, i.e. giving the description and the characterization of a crests line which specify it.

Crests line description and characterization

On the base of line images, we can adopt the following definitions for a crests line (resp. valley), which are well adapted to the algorithms we will expose :

Definition 1 : *A crests line (resp. valley) occurs when there is a simply connected sequence of pixels having grey-tone intensity values which are significantly higher (lower) in the sequence than those neighbouring the sequence* (Haralick, 1983).

Definition 2 : *The valley is defined as a "concave scene of waters convergence". By duality the crest is defined as a "convex scene of waters convergence of anti-streaming"* (Riazanoff and al., 1987).

We have chosen a naturalist approach of a picture relief by considering :

- ***how an extreme line can be seen in relation to the other points of the relief*** : more precisely, we search how to reach naturally the crest line from other points of the relief. We have chosen to leave from a point opposite to a crests line, therefore a valley point (local minimum); to reach the aimed line, the moving must be done according to a growing in altitude "perpendicularly" to the lines surrounding this valley point.

- ***how it can be followed from the "ideal" points*** : we imagine that we are walking on crests line in a relief and we ask how to move naturally on this line, then we are led to use S. Riazanoff and al. reflection which says : "we'll walk on points presenting a convexity in a direction", from a particular point (verifying a property given a priori) which permits to initialize the movement.

Presentation of the methods

Definitions

1/. Let V be the function which we'll call function of neighbouring defined for any pixel p by :

$$V(p) \subset V_8(p) \cup \{p\} \qquad (3)$$

2/. We note ad_1 and ad_2 the adherence of the pretopological structure (E, ad_1) and (E, ad_2) defined respectively by :

$$\forall A \in \mathcal{P}(E) \quad ad_1(A) = \{p \in {}^cA \,/\, \forall q \in V(p) \cap A, f(q) \le f(p)\} \cup A \qquad (4)$$

$$\forall A \in \mathcal{P}(E) \quad ad_2(A) = \{p \in E \,/\, \exists q \in A, p \in V(q)\} \qquad (5)$$

where ${}^cA$ is the complement of A in E;

3/. Let attr the function defined from E to R by : $\forall p \in E, \quad attr(p) = \max_{q \in V_8(p)} (f(q) - f(p))$ (6)

Principles of the methods

We'll only explain the methods relative to crest lines detection; for the thalwegs, it's sufficient to detect the crest lines on the inverse relief.

<u>Principle of the first method :</u>

In this algorithm, we use the pretopology we've defined in the previous section with the adherence ad_1. The principles of the algorithm are the followings :

a- Determination, in a first time, of the "ideal" points i.e. the local minima points of the grey function.

b- Construction in parallel of the successive adherences of these points.

c- When a point belongs at the same time to two different classes, it will be qualified as a crests line point; consequently it will be "neutralized", and the function of neighbouring will be re-evaluated without considering this point.
d- The algorithm stops when the stability for each one of the evaluated adherence has been reached.
The crests lines are identified as the algorithm goes on by the property of simultaneous belonging to at least two adherences associated to different ideal points.
Thus, the process of picture points grouping follows an upward slope in relation with the values of the grey function; and the adherence intersection points form in fact, according to the definition of a crests line suggested by R.M. Haralick, a points sequence significantly higher than the sequences neighbouring it. Indeed, a point included in one of the intersections can be considered as belonging to an altitude path surrounded on both sides by lower zones; these zones are in fact the adherences built successively.

Principles of the second method :
For the second algorithm, we use the pretopological structure defined with the adherence ad_2 and we defined an attraction structure on the pixels; this structure permits to extract a new pretopology denoted $\mathfrak{N}ad$ which will determine the final classes.
For any pixel p we have :
* if attr(p)<0, the pixel q_0 which corresponds to that maximum "***attracts***" p and so $p \in \mathfrak{N}ad(q_0)$,
* if attr(p)>0, p is a local maximum; it 's not attracted by any point; then p is called a "***free attracting point***",
* if attr(p)=0, let $Z=\{q \in E,\ attr_p(q)=0\}$, any $q \in Z \cap \mathfrak{N}ad(\{p\})$ is eliminated; and if exist $q \in Z$, $q \notin \mathfrak{N}ad(\{p\})$, then one of these q is chosen to be the "***attracting point*** " of p, else p is called a "***free attracting point***".
So we superimpose an attraction structure on the image in which each point p may be in one of the three following situations:
1) p belongs only to its own new adherence,and this one contains points different from p; then p is called a "***free attracting point***";
2) $\mathfrak{N}ad(\{p\})=\{p\}$ et p belongs to the new adherence of other points; then we say that p is a "***hanging and tied point***";
3) $\mathfrak{N}ad(\{p\}) \neq \{p\}$ and p belongs to the new adherence of other points; then p is called a "***tied attracting point***".
Once that structure has been placed in situation, crest lines are determined by constructing successive new adherences for the "free attracting points", up to the stability of those new adherences, i.e. the determination of the smallest integer n(p) such that :

$$\mathfrak{N}ad^{n(p)}(\{p\}) = \mathfrak{N}ad^{n(p)+1}(\{p\}) \quad (7)$$

Thus ***the crest line containing p is the set of points $\aleph(p)$ to which p belongs and defined by :***

$$\aleph(p) = \mathfrak{N}ad^{n(p)}(\{p\}) \setminus \{\text{hanging and tied points}\} \quad (8)$$

Algorithms

Algorithm 1
Let $\mathcal{C}$ be the set of marked points (crests).
1. Initial step (*find all local minima points and mark them as belonging to the classes* A_i^0 *which are empty at the beginning; i is the number of initial classes determined*)
for each pixel p of the image do if p is a local minimum then $A_i^0 = \{p\}$
2. intermediate step (*the local minima points which are neighbours are grouped together in a class; thus the process will begin with a minimal zone*)
for any couple (i,j) do if $p \in A_i^0$ and $q \in A_j^0$ and p, q are neighbours then put q in A_i^0

3. construction step (iterative)

α) for each class do (*update the neighbours function necessary to calculate the new adherence, by neutralising all the points already classified in* $\mathcal{C}$)

for any pixel $p \in A_i^k$ do $V(p) = (V_8(p) \cup \{p\}) \setminus \mathcal{C}$ and evaluate $A_i^{k+1} = ad_1(A_i^k)$

β) for any couple (i,j), i≠j do $\mathcal{C}=\mathcal{C}\cup(A_i^{k+1} \cap A_j^{k+1})$ (*put all the intersection points i.e. crests points in* $\mathcal{C}$)

γ) if i exist such as $A_i^{k+1} \neq A_i^k$ then go to α; if any i $A_i^{k+1} = A_i^k$ then stop the process (*the algorithm stops only if all the classes* A_i^k *are closed*)

Algorithm 2

Let $\mathcal{C}$ be the set of crest lines.

(*calculate the adherence function* ad_2 *in each point of the image)*

0.for each pixel p of the image do $ad_2(\{p\}) = V(p) = V_8(p) \cup \{p\}$

1. new pretopology determination (*first sweeping of the image with searching the "attracting" and "attracted" for each point, and then putting all "free attracting points" in* $\wp$ *set*)

for each point p in the image do * $\mathcal{N}ad(\{p\}) = \{p\}$

* calculate the $attr(p) = \max_{q \in V_8(p)} (attr_p(q))$

if $attr(p) < 0$ then let be q realizing this maximum and q attracts p so put p in $\mathcal{N}ad(\{q\})$

if $attr(p) > 0$ then p is a free attracting point put p in $\wp$

if $attr(p) = 0$ then let $M = \{q \in G(p) / attr_p(q) = 0\}$ and $L = \{ r \in M / r \in \mathcal{N}ad(\{p\})\}$

if $M \setminus L \neq \varnothing$ then let be one $q \in M \setminus L$ and put p in $\mathcal{N}ad(\{q\})$;

else p is a free attracting point; put p in $\wp$

2. "*hanging and tied points*" determination: for any point p do if $\mathcal{N}ad(\{p\})=\{p\}$ then put p in $\mathcal{L}$

3. exploration (*calculate the successive adherences of the "free attracting points" until stability*). for any point $p \in \wp$ do

a) $\aleph(p) = \mathcal{N}ad^n(\{p\})$

b) n = n+1; compute $Nad^n(\{p\})$; if $\aleph(p) = \mathcal{N}ad^n(\{p\})$ then go to c, else go to a

($\aleph(p)$ *represents the crests line passing by the "free attracting point"* p)

c) if $\aleph(p)=\{p\}$ then p is an isolated point, else $\mathcal{C} = \mathcal{C} \cup \aleph(p)$

4. determination of all crest lines $\mathcal{C} = \mathcal{C} \setminus \mathcal{L}$

Applications

We have tested our algorithm on two types of images :

a- images taken by the "DIFFRACTO" method on composite materials with glassfibers (BMC),

b- images taken on cloth samples at exit of a cloth-drier.

The results presented here correspond to the processing realized by our two algorithms on the images given in figure 1. Figure 2 shows the results obtained by application of the first algorithm followed by a thresholding on negligible depth lines. We obtain one thickness lines; the second operation reduces the initial net density, and then provides worbable results for an ulterior analysis (rose of directions). In figure 3, we find the results obtained with the second algorithm; the detected lines have a variable and upper than one thickness. These results are more interesting than the previous ones because they exactly exhibit the clear and dark zones the distribution of which is caracteristic of materials surface finish flaws for the first image and for the crumble of the second image.

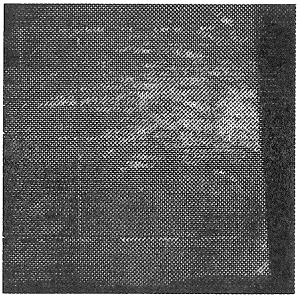
Fig.1.a

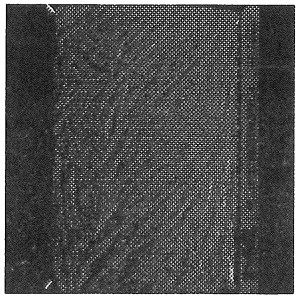
Fig.1.b

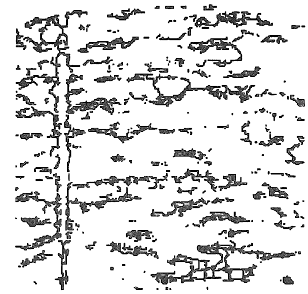
Fig.2.a

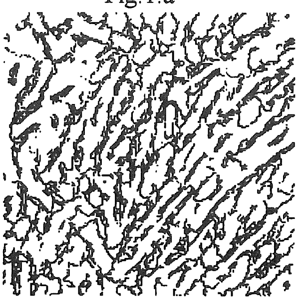
Fig2.b

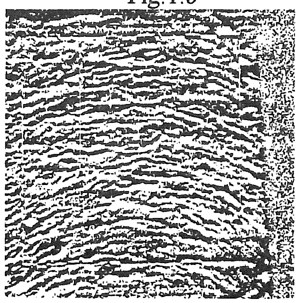
Fig.3.a

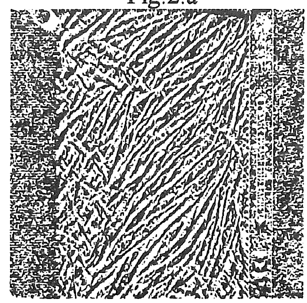
Fig.3.b

Fig.1. a- original image of the composite material; b-original image of the cloth

Fig. 2. a Detection of the crest lines in the original image a and b by the first algorithm.

Fig. 3. a. Detection of the crest lines in the original image a and b; by the second algorithm

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