Perceptual Grouping of Continuation: Application for Satellite Images

P. Montesinos
H. V. Blanc

EERIE/LERI
Parc scientifique G. BESSE
NIMES, f-30000

July 22, 1994

Abstract

We present a method of grouping edge elements upon the relation of smoothed continuity. This method is based upon the optimization of a quality function of curvature and edge intensity, from a local to a global level. It is implemented with a network of locally-connected processing elements. This method was first designed to deal with dot images and then was applied to the problem of road extraction in satellite images. The extension to satellite images has been achieved by means of constraints from low level vision algorithms and a dynamic exploitation of results of the grouping process. This method copes with a complex combinatorial problem allowing an efficient and parallel solution to be found. Experimental results on synthesis and natural satellite images show the validity of the approach and its possible incorporation into general computer vision systems.

1 Introduction

Since 1923, psycho-visual experiments [13] have shown that human perception is driven by grouping phenomena of image primitives in more complex forms. These groupings result from very general global relations such as symmetry, continuation, similarity, object-background separation, etc. Perceptual organization is not only the result of local computations but also of a global perception of a scene. Perceptual grouping, and more generally, Gestalt psychology says that perception is made as a whole.

In image analysis, Lowe [5] has used some of these processes to show that they were useful to prune the search space of the interpretation. In particular, he has shown that the complexity of the relations between subparts of the grouping can improve the saliency of a grouping. Much work in this field of investigation has been carried out. It mainly belongs to two different techniques: algorithmic techniques [4], [7] [12] and optimization techniques [9], [3], [10]. In this paper, we are interested in a technique of optimization.

Problems of perceptual organization are often encountered with contour segmentation of images. First, the resulting contours are discontinuous and secondly, some of them have no corresponding object in the image. Causes of these problems are numerous: weak strength of the edge, noise, shadows, texture, possible overlaps, etc. Within this framework, we have tried to imitate the grouping processes of human vision for the continuity and closure relations. Several smoothness and continuity functions have been tested [8], [11] to deal with this problem. Sha'ashua [10] has shown that it was possible to group together contour elements according to a smoothness and continuity criterion. This technique consists in looking for a smooth and continuous path among a subset of all the possible paths in the image. In this paper, we use the technique of recursive optimization developed by Sha'ashua and Ullman, to which we make some important modifications. First, our method can deal with dot images instead of segment images, i.e. no orientation information from edge detection is available. Second, our optimization algorithm is more general and more efficient, especially because of its ability to take into account multiple points. This feature is especially interesting for the search of open shapes (for example: lines in satellite images). Third, our quality criterion introduces a notion of co-circularity computed with a measure of the second order derivative of the curvature. We show that this point can considerably improve the strength of our method. We then show how to take constraints from low level vision: estimated orientation, corner points ratio primitive on background density, etc. into account. This enables us to deal with images the noise of which is not white as well as real edge detection images. Finally, we apply this technique to real satellite images using dynamic information extraction from the network based on contour chain primitives.

This paper is divided into seven parts. Psychological results on the human visual system are summarized in section 2.1. The techniques of exploration and evaluation of the paths and the way the quality function is made recursive are described in section 3. The optimization algorithm of the quality function with a network of locally-connected processing elements is presented in section 4. Details of the implementation are given in section 5. Precise results obtained on synthetic and real images are presented in section 6.

2 Previous work

2.1 Perceptual Organization: a psychological point of view

Since 1923, grouping phenomena of image primitives into more complex shapes without prior knowledge of the scene, have been demonstrated in the human visual system. These groupings are a result of a structuring of information on the basis of general relations such as continuation, symmetry, similarity, object-background separation, etc. These experiments are at the origin of the psychology of the shape called "Gestalt Psychology".

The principal argument of "Gestaltists" can be presented in this way: a retinal image is composed of a set of "levels of brightness" points, carrying no information about the object to which they belong. The capacity to see different objects results from a structuring of the information by the brain. Numerous simple examples demonstrate the validity of these assumptions: a human eye will see with evidence co-linear or co-circular line segments on a background of segments of random position and orientation.

For "Gestaltists", visual perception is made as a whole: the human eye perceives scenes globally rather than as a sum of subparts. Here, too, demonstrations of this phenomenon are abundant: the perception of an object or of its contours can change according to whether we look at a scene globally or partially.

What role can perceptual organization play in human vision?
Experimental psychology gives elements of the answers. In experimental psychology, Lowe [5], shows an example, where two drawings of line segments, representing a bicycle, are proposed to two groups of several persons. In the first drawing, all the possibilities of groupings have been removed. It is

extremely difficult to see the bicycle and the recognition time is quite long. In the second drawing, the "wheel" grouping remains possible and the recognition time is greatly reduced. This experiment shows that perceptual organization is a way to simplify the interpretation process. Moreover, perceptual organization is an essential process for vision and scene interpretation.

2.2 Perceptual Organization and Computer Vision

2.2.1 Marr's work

The idea of using perceptual organization techniques in computer vision is not a recent phenomenon. In 1976, Marr [Marr 76] proposed the idea of "primal sketch" which should contain not only edge processing information but also sets of groupings of image primitives in curves and lines. The main problem is that no implementation was proposed here and the use of perceptual organization in computer vision became popular later.

2.2.2 Lowe's work

Lowe [5], introduces a formalism to describe the saliency of a grouping in terms of probabilistic properties of the association of its components. He cluster groupings into two classes: accidental and causal. Each grouping carries statistical information represented by its probability of accidental occurrence, measuring its saliency. He uses perceptual organization to interpret monocular $3D$ scenes. In an image, from a certain point of view, accidental groupings generated by accidental positions of the objects of the scene (groupings between primitives belonging to different objects) and causal groupings (groupings between primitives belonging to the same object) co-exist. A grouping, the probability of accidental occurrence of which is small, is very significant at the scene level. Relations which are of great significance are those which remain invariant over a wide range of viewpoints, for example: co-linearity, symmetry, proximity, etc.

2.3 Parent and Zucker's work

This work has been carried out within the framework of curve detection in noisy images [15], [8]. The problem dealt with here is perceptual organization for the continuation relation. Their main contribution is in the definition of quality functions taking into account the saliency of curves as the human eye would do. These functions use co-circularity, curvature, derivative of curvature, grey levels, etc.

2.4 Hérault's work

Perceptual organization is [3] tackled by a global approach of combinatorial optimization. Hérault uses a quality function based on co-circularity defined by Parent and Zucker for the qualification of the saliency of curves. Co-circularity is calculated with contour information and the orientation of edge points. The approach here is essentially global and the optimization is achieved by the methods of annealing and mean field annealing.

2.5 Sha'ashua's work

Sha'ashua [11] [10] has developed an original approach of optimization from a local to a global level. He shows that recursive quality functions based on curvature and grey levels of a curve can be built. The optimization method is iterative, and the the quality function becomes more global as the iterations grow. Sha'ashua defines a deterministic optimization method, from a local to a global level implemented with a network of locally connected processing elements. His method deals with segment images on which orientations are known.

3 A quality function

As we are interested here in an optimization technique, we have defined a quality function for the perceptual grouping of continuation. This function is built with several terms or expressions that can deal with the curve features we consider: smoothed continuity, co-circularity. We first find a global term combining the strength of edges and curvature. This term is defined recursively from a local to a global level which is necessary for global optimization. It combines both image information and curve information. We then find local terms carrying curve information (co-circularity) or image information when it is available (for example, edge orientation or corner points). These terms can be seen as local constraints in the optimization process. The image constraints force the curves to respect certain structures (tangents) as the curve constraints act on the shape of the curves themselves (co-circularity). The sum of all these terms gives a criterion which is maximum for a long and straight (or circular) path of high intensity.

3.1 Definition of the global term

Since we want to define a quality criterion based on smoothed continuity, we combine curvature and edge intensity. The total curvature of a path (γ) gives us local curvature terms which are going to be used in the quality criterion.

$$C = \exp\left(- \int_{\gamma} \left(\frac{d\theta}{ds}\right)^2 ds \right)$$

and, in discrete terms:

$$C = \prod_{i=2}^{M-1} f_{i-1,i+1}$$

where M is the number of pixels of the path, and $f_{i-1,i+1}$ a measure of curvature between three consecutive pixels along the path (seen as a parametrized curve).

More precisely:

$$f_{i-1,i+1} = \exp\left(- \frac{2\,\theta\,\tan\left(\frac{\theta}{2}\right)}{\Delta S} \right)$$

where θ represents the angle between $i-1$ and $i+1$ through i: $\theta = 2\pi - \widehat{i\text{-}1,i,i\text{+}1}$, and ΔS

the distance between the two pixels $i-1$ et $i+1$ (by i). Thus, we have $0 \leq f_{i-1,i+1} \leq 1$, and $f_{i-1,i+1} = 0$ if $\theta = \pi$, $f_{i-1,i+1} = 1$ if $\theta = 0$.

Let σ_i be the grey level of the pixel i of a path. In order to evaluate the "quality" of the path, we define the first global term of the quality function depending on σ_i and $f_{i-1,i+1}$.

The quality factor of the curve entering on the left at i is defined as:

$$\begin{aligned} F_l(i) = \; & \sigma_{i-1} \\ & + \rho f_{i-2,i}\sigma_{i-2} \\ & + \rho^2 f_{i-3,i-1} f_{i-2,i}\sigma_{i-3} \\ & + \cdots \end{aligned}$$

where ρ is an attenuation term ($0 < \rho < 1$). Similarly, we define a quality factor of the right portion of the curve entering at i, $F_r(i)$.

We then define a bi-lateral quality function at i as a linear combination of first order terms (σ_{i-1}, σ_{i+1}) and lateral quality functions ($F_l(i)$ and $F_r(i)$).

$$\begin{aligned} F(i) = \; & (2\alpha - 1) \; (\sigma_{i-1} + \sigma_{i+1}) \; f_{i-1,i+1} \\ + \; & (1-\alpha) \; (F_l(i) + F_r(i)) \; f_{i-1,i+1} \end{aligned}$$

where α is a weighting factor taking its values between 0 and 1. This definition allows the quality function to be less sensitive to the local influence of noise, for small values of α.

With this definition, $F(i)$ can be rewritten as a sum of first order terms and bigger ones, weighted respectively by the factors α and $(1 - \alpha)$:

$$\begin{aligned} F(i) = \; & \alpha \, (\sigma_{i-1} + \sigma_{i+1}) \; f_{i-1,i+1} \\ + (1-\alpha) \, [\; & \rho \; (f_{i-2,i}\sigma_{i-2} + f_{i,i+2}\sigma_{i+2}) \\ & + \rho^2 \; (\cdots) \\ & + \rho^3 \; (\cdots) \\ & \vdots \\ &] \; f_{i-1,i+1} \end{aligned}$$

The first order term is a term which depends on the local grey level of the curve. Otherwise, the other terms are representative of a long distance measure of the quality of the curve. The factor ρ defines the way in which long distance portions of curves influence the pixel i.

We now define the global quality function of a path as the sum of the local quality functions ($F(i)$) for all the pixels of the path.

$$F_\gamma = \sum_{i=1}^{M} F(i)$$

3.2 Recursive computation of the global quality criterion

The function we have defined can be recursively computed by a progressive lengthening of the path. We will first look at the 1-D case then at the 2-D case.

3.3 1-D case

We first limit ourselves to parametrized curves. We will see in a later subsection how to derive this calculation in the two-dimensional case. The quality function at length n is defined as the sum of the n first terms of F_l (resp. F_r). This number n designates the length of the portion of the considered path.

$$F_l^{(n)}(i) = \begin{cases} \sigma_{i-1} & \text{for} \quad n = 0 \\ \sigma_{i-1} + \sum_{m=i-n-1}^{i-2} \left[\sigma_m \, \rho^{i-m-1} \prod_{k=m+1}^{i-1} f_{k-1,k+1} \right] & \text{for} \quad n \neq 0 \end{cases}$$

Such functions can also be written with recurring series depending on the step n and the position along the path.

$$F_l^{(n)}(i) = \begin{cases} \sigma_{i-1} & \text{for} \quad n = 0 \\ \sigma_{i-1} + \rho \, f_{i-2,i} \, F_l^{(n-1)}(i-1) & \text{for} \quad n \neq 0 \end{cases}$$

We define F_r in the same way.

3.4 2-D case

In the more general case of two dimensions, we must take into account all the possible paths at a given pixel.

Let :
P be a pixel,
$V(P)$ a neighboring system and
$N = Card(V(P))$ the size of $V(P)$.

For such a pixel with its neighboring system, there are two pixels (belonging to $V(P)$) which define two paths entering P. Moreover, $N(N - 1)$ possible pairs of pixels exist (in $V(P)$), under the constraint that we must have two distinct entering paths for a pair of pixels.

This 2-D case differs from the previous one (1-D), in that numerous possible paths can "cross" a same pixel. In order to globally optimize the quality function over the image, we have to select one or several paths with maximal quality functions. Locally, for each pixel P, we must compute the best paths crossing it. Therefore, for each path entering P, we look for another well-defined entering path such that the local quality function is maximal for this pair of pixels. Therefore we have to select N pairs of pixels from among $N(N-1)$ possible ones.

For that calculation, we also need the information of exiting paths (a path crosses a pixel). We construct a binary connection matrix, defining the N paths crossing each pixel. Each pixel has its associated connection matrix (see equation 3).

Let P, Q, $\tilde{Q}$ be three pixels, such that $(Q, \tilde{Q}) \in V(P)^2$, Q entering P and $\tilde{Q}$ leaving P along a path.
If i and o are their two associated directions seen from P, we define :

- $F_i(P)$ the quality function entering P along the direction i.
- $Prec(i, P)$ the function, which gives, for a pixel P and an input direction i, the pixel Q entering P along i.
- $Succ(o, Q)$ the function which gives the pixel P, such that Q enters P along o.
- $\bar{\imath}$, the mirror orientation of i: if Q enters P along i, P leaves Q along $\bar{\imath}$ ($\bar{\imath}$ is the output seen from Q along the considered path).

So:

$$
\begin{aligned}
Q &= Prec(i, P) \\
\tilde{Q} &= Succ(o, P) \qquad P = Succ(\bar{\imath}, Q)
\end{aligned}
$$

These functions are easy to construct and their definition does not make any use of quality functions; they simply link directions to pixels.

On the contrary, we have to define two other functions which give, for a pixel P and a exiting direction (resp. entering), a correct entering direction (resp. exiting). These functions use the quality functions at step n and play a role in the computation of the quality functions at step $n + 1$ (section 3.1 deals with these points in detail). The aim is to associate the best exiting direction with a given entering direction and inversely, using the current quality functions. These functions make an implicit use of the connection matrices.

Let *exiting* and *entering* be those functions, such that :

- $o = exiting(i, P)$: a function which gives, for a pixel P and an entering direction i, the exiting one along the path crossing.
- $i = entering(o, P)$: a function which gives, for P and an exiting direction o, the entering direction along the path crossing.

In 2-D, we obtain:

$$
F_i^{(n)}(P) = \begin{cases} \sigma_Q & \text{for} \quad n = 0 \\ \sigma_Q + \rho\, f_{e',\bar{\imath}}\, F_{e'}^{(n-1)}(Q) & \text{for} \quad n \neq 0 \end{cases} \tag{1}
$$

with:

$$
e' = entering(\bar{\imath}, Q) \qquad (e' \text{ and } \bar{\imath} \text{ are seen from } Q).
$$

Experiments have shown that connecting inputs together results in less sensitivity to noise than just connecting inputs to outputs (input paths come from a long distance as output paths are influenced by the local noise). In this sense, we optimize a two-sided quality function made of two lateral entering contributions. In two dimensions, the first global term is defined as:

$$
\begin{aligned}
F_{i,o}^{(n)}(P) = F_{Q,\tilde{Q}}^{(n)}(P) = & \quad (2\alpha - 1) \ \left(\sigma_Q + \sigma_{\tilde{Q}}\right) f_{i,o} \\
& + \ (1 - \alpha) \ \left[F_i^{(n)}(P) + F_o^{(n)}(P)\right] f_{i,o}
\end{aligned} \tag{2}
$$

where $\tilde{Q}$ and o represent another entering path: this means that we use the entering quality functions in P from the direction o.

3.5 Use of more global information

In certain cases of very noisy images or images containing non-white noise, it is possible to take into account more global grey level information. In formula 2, we replace a gaussian mean of grey level in the direction of inputs instead of just the grey level of the closed pixels: σ_Q and $\sigma_{\tilde{Q}}$ becomes $\tilde{\sigma}_Q$ and $\tilde{\sigma}_{\tilde{Q}}$ (see fig: 2.3 and 3.3). This point allows the grouping process to connect large holes and to be less sensitive to the noise.

3.6 Introduction of constraints

3.6.1 Local co-circularity constraint

We define a criterion of local co-circularity based on the second derivative of the orientation in regard to the curvilinear coordinates ($d^2\theta/ds^2$) of the curve. Due to numerical approximation, we prefer to "derive" the local curvature terms ($f_{i,j}$); we obtain a local 1-D parametric term defined as:

$$\kappa_{j-2,j-1,j+1} = \frac{|\, \mathrm{sgn}(\theta_{j-1})\, f_{j-2,j} + \mathrm{sgn}(\theta_j)\, f_{j-1,j+1} \,|}{2\, \Delta s}$$

where $j-2, \cdots, j+1$ represent four consecutive pixels along a curve and Δs represents the distance along the curve between $j-2$ and $j+1$. A symmetrical criterion is derived by taking the mean of two terms " κ " around the reference pixel j.

$$C_1(j) = \frac{1}{2}\left(\kappa_{j-2,j-1,j+1} + \kappa_{j-1,j+1,j+2}\right)$$

In the 2-D case, the pixels are defined by the use of the function *input*.

3.6.2 Local orientation constraint

Up to now, we have only considered dot images where no orientation information is available. We want to extend our method to segment or edge images with a known orientation of edge points. Let β_P be the orientation of an edge at a given pixel P of the image and θ_P the orientation of the tangent of a curve crossing at P. The local orientation constraint can be expressed by:

$$C_2(P) = \exp[-\tan(|\beta_P - \theta_P|)]$$

3.7 Complete quality function

We define the complete quality function as a linear combination of the first term of the global quality function and the preceding constraints.

$$\mathcal{F}_{i,o}(P) = \mathcal{F}_{Q,\tilde{Q}}(P) = F_{i,o}(P) + \delta\, C_1(P) + \xi\, C_2(P)$$

Where δ and ξ ($\delta, \xi \in [0,1]$) are coefficients weighting the different constraints.

4 Optimization of the quality function

Most of the problems occurring in perceptual organization topics are solved by optimization of an energy function. The proposed techniques are often global (Hopfield networks, some Markov processes). We propose here a local method which is based on the use of locally-connected networks which globally optimize the quality function. As this function is not convex, we optimize it in several stages, from a local to a global level. Each stage corresponds to an order of the global nature of the paths crossing one pixel.

The optimization is implemented by a uniform, locally-connected processing element network, with one processing element per pixel. At each iteration, the network optimizes the quality functions, the level of global nature of which increases with the length of the portion of path considered (this portion grows with the iterations). With that aim in mind, at each step and at each pixel, we connect entering paths in order to maximize the global quality function. This mechanism makes the global nature level of quality functions increase along the iterations. Section 4.1 renders the computation of the connections explicit.

4.1 Computation of the connections

The connection matrices are binary square matrices, of size $N \times N$, the lines of which represent the entering pixels and the columns the exiting pixels. The connections are computated in two steps: inputs toward outputs then outputs toward inputs.

4.1.1 Connecting inputs toward outputs

For each pixel P and each entering Q, we look for an exiting pixel $\bar{Q}$ which maximizes the quality function at step n in (P): $\mathcal{F}^{(n)}_{Q,\bar{Q}}(P)$

Let $C^{(n)}(P)$ be the connection matrix for a given pixel P at step n . Its elements are of the following form:

$$C^{(n)}_{i,o}(P) = C^{(n)}_{Q,\bar{Q}}(P) = \begin{cases} 1 \text{ if} & \mathcal{F}^{(n)}_{Q,\bar{Q}}(P) = \max\limits_{\bar{Q}' \in V(P) \setminus \{Q\}} \mathcal{F}^{(n)}_{Q,\bar{Q}'}(P) \\ 0 \text{ otherwise} \end{cases} \tag{3}$$

One can notice that the connection inputs toward outputs is not symmetrical: for an entering direction i and a pixel P, exactly one exiting direction exists, *output* (i, P) the quality function of which is maximum but the converse is false. In fact, for a given exiting direction o, there are two possible cases: several entering directions may exist and a corresponding input does not exist.

4.1.2 Connecting outputs toward inputs

We are going to define here the *entering* function ($i = entering(o, P)$) which gives, for a given output direction o and a pixel P, a corresponding entering direction i.

Case of multiple inputs:

In the case of multiple inputs, we have to make a choice between L possible inputs: we define the *entering* function, such that the quality function, in P with this output o, is maximal at the input i_l taken among the L possible inputs.

More formally:

We have:	$\bar{Q} = Succ(o, P)$
let:	$E(\bar{Q}) = \left\{K_m \in V(P)\backslash\{\bar{Q}\} \mid C^{(n)}_{K_m,\bar{Q}}(P) = 1\right\}$
and:	$L = Card(E(\bar{Q}))$

Let $K_l \in E(\bar{Q})$ such that: $\mathcal{F}^{(n)}_{K_l,\bar{Q}}(P) = \max_{K_m \in E(\bar{Q})} \mathcal{F}^{(n)}_{K_m,\bar{Q}}(P)$

We can now define the function *entering*: $i_l = entering(o,P)$ such that K_l is the entering neighbor in P along direction i_l, ($K_l = Prec(i_l, P)$)).

Case of no input:

In this case, a given output $\bar{Q}$ has no corresponding input, we can still define such a correspondence:

- We compute the global maxima of the quality function $\mathcal{F}^{(n)}_{Y,Z}(P)$ independently of any output. This computation leads us to two symmetric solutions giving two pairs (Y, Z) and (Z, Y) corresponding to the two directions y and z respectively.
- We define the function *entering* as:

$$entering(o,P) = \begin{cases} y & \text{if} \quad \mathcal{F}^{(n)}_{Y,Q}(P) > \mathcal{F}^{(n)}_{Z,Q}(P) \\ z & \text{otherwise} \end{cases}$$

4.2 General algorithm

4.2.1 Optimization

For each value of step n, the network carries out two tasks:

- It updates the quality functions (see equation 1) on the basis of the connections.
- It updates the connections with the help of the current quality function.

Through this propagation of the data in the network, the future connections will be calculated with more and more global information.

4.2.2 Selecting the best paths

Along the iterations, the connections are locally organized in such a way that some salient paths, distributed throughout the network, can emerge. We must now find these paths and select some of the best or just the optimal one. To achieve this, a recursive following algorithm explores these paths and globally evaluates them.

For a given pixel, we want to avoid the exploration of directions which do not seem promising, so we have to choose one direction from among the neighborhood $V(P)$. In order to initialize this algorithm, we use the heuristic which consists in selecting the direction maximizing the local quality function.

We present here the general algorithm of optimization and selection:

Algorithm:

- **Initialization** of quality functions and connections at step 0 (n = 0).
- **Iterations:**
  - **For each pixel,**
    - Update of the quality function.
  - **For each pixel,**
    - Local optimization of the quality function: computation of the connections.
- **Following and selecting** the best path.

In the case of synthetic images, a simple following algorithm works (since we have one path per pixel, we choose the one having the maximum quality). It is not the same situation when we have to deal with complex real images which may contain more than one object and several interesting groupings, as is the case of road extraction in satellite images. Here, we have to select several groupings of which some are sub-maxima [1]. In this case, we must use another kind of information to retrieve the interesting groupings: contour chains (obtained by an "edge following" algorithm in 8-connexity).

We use the following algorithm:

Algorithm:

- **Computation of the quality function** of each contour chain
  (a contour chain is a portion of a path).

- **Thresholding** of the chains with respect to their quality,
  (a chain included in a larger structure has a strong quality).

- **The remaining chains are put in a stack.**

- **For each chain in the stack:** follow-up of their extremes up to another chain.

  - If the new chain passes coherence tests (orientation, junction point)
    Then:
    - **Fusion** of the two chains.
    - **The stack is updated.**

4.3 Convergence

In the 1-D case, the convergence of the series $F^{(n)}(j)$ is obvious, because it is a monotonic series bounded by a geometric series generated by the factor $\rho < 1$. In the 2-D case, the problem is more complex because connections move as the iterations increase and the series calculated here are non-monotonic. We verify experimentally on several images that the values of the parameters ρ and α do not have a strong influence on the convergence of the algorithm and on the results. Generally, for values of ρ less than 1, "convergence" to a good solution is quite well ensured (two consecutive solutions are quite similar). Therefore, we notice that for very noisy input images convergence sometimes becomes difficult; the network oscillate between several different salient solutions.

5 Implementation

The 8-connexity does not supply enough sampling angles to allow the precise computation of the curvature of a path to take place. We use a system of 16 neighbors: 8 coming from the 8-connexity, and 8 neighbors defined by the moves of a knight in a chess game. (see Figure 1). This neighborhood offers an intermediate structure between the small 8-neighborhood and bigger ones and it does not provide a high level of algorithmic complexity (dimension of $F_{i,o} = 16 \times 16$).

6 Results

We present here several results of groupings on synthetic images (fig: 2.1, 2.2, 2.3, 4.1), and also on a natural satellite image (fig: 5.1 5.2). Synthetic images (fig: 2.1, 2.2, 2.3, 80×80) represent an ellipse where 40% of the pixels have been removed by white noise. Pixels of white noise have then been

	10		9	
11	3	2	1	8
	4	P	0	
12	5	6	7	15
	13		14	

Figure 1: *Neighboring system*

added to these images at: 5% , 10% and 20% on the global image. The image (fig: 4.1, 100×100) represents a smoothed noisy hand drawing with a shape which is more complicated than that of a circle or an ellipse. We show with real images how our method is able to deal with the problem of road extraction (more generally, line extraction) in satellite images (fig: 5.1, 5.2). These two images (70×130) have been extracted from a larger one (512×512). The image (fig: 5.2) shows the result of line extraction [14] on the image (fig: 5.1) (The holes in the lines are due to the fact that images have been processed and thresholded globally). The results obtained both on synthetic and natural images demonstrate the strength of the method and its possible use for natural scene interpretation.

7 Conclusion

We have presented an optimization method from a local to a global level for the perceptual organization of continuation. Our results show that these recursive optimization methods are well adapted to the problem of perceptual organization for the relations of continuation and closure. For human perception, groupings are made according to a global criterion. One of the attractive features here is that we implement a technique of global optimization with exclusive local computations. For this reason, our method represents a small computational complexity. This optimization method - from a local to a global level - is naturally implemented with a network of locally-connected processing elements. On the one hand, it allows a complex combinatorial problem to be solved efficiently and, on the other hand, the algorithms are simple and can easily be implemented in parallel.

The quality of the results obtained on different types of images demonstrates the attractiveness of the method. The study of real images shows that it is necessary to take into account constraints from image processing (computed before perceptual grouping). For example: the image orientation of contours, corner detection, as well as a new kind of information: contour chains which give a dynamic aspect in the search for groupings.

In the future, we are going to work on the introduction of new constraints in the quality function: corner points, constraints coming from a multi-scale analysis, etc.

References

[1] **H.V. Blanc.** *Application of Perceptual Grouping to the Extraction of Roads on Satellite Images.*

DEA Report, University of Montpellier II, France, June 93 (*in french*).

[2] R. Deriche.
Using Canny's criteria to derive a recursive implemented optimal edge detector. Int. J. Comput. Vision 1, 167-187, 1987.

[3] L. Hérault.
Réseaux de neurones récursifs pour l'optimisation combinatoire. Thèse de doctorat, Institut National Polytechnique de Grenoble, Février 1991.

[4] R. Horaud, F. Veillon, T. Skordas.
Finding Geometric and Relational Structures in an Image. First European Conference on Computer Vision, 23-27 April 1990, Antibes, France.

[5] D. G. Lowe.
Perceptual Organisation and Visual Recognition. Kluwer Academic publisher, Hingham MA 02043, USA.

[6] R. Mohan, R. Nevatia.
Segmentation and Description Based on Perceptual Organization. Technical Report IRIS#249, Institute for Robotics and Intelligent Systems, University of Southern California, January 1989.

[7] P. Montesinos.
Une méthodologie en vue de l'interprétation automatique d'images aériennes: application à la détection des bâtiments. Thèse de doctorat, Université de Nice Sophia-Antipolis, février 1990.

[8] P. Parent, S. W. Zucker.
Trace Inference, Curvature Consistensy, and Curve Detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol 11, no. 8, August 1989.

[9] T. J. Sejnowski, G. E. Hinton.
Separating Figure from Ground with a Boltzmann Machine. M. A. Arbib and A. R. Hanson Editors, 1988, MIT Press.

[10] A. Sha'ashua, S. Ullman.
Grouping Contours Elements Using a Locally Connected Network. Neural Information Processing Systems, 1990.

[11] A. Sha'ashua, S. Ullman.
Structural Saliency: The Detection of Globally Salient Structures Using a locally Connected Network. IEEE, Second International Conference on Computer Vision, 5 dec. 1988, Tampa Florida.

[12] Y. C. Shiu.
Experiments with Perceptual Grouping. SPIE, Proc. Intelligent Robots and Computer Vision IX: Algorithms and Techniques, 5-7 Nov. 1990, Boston, Massachusetts, Vol 1381.

[13] M. Wertheimer. *Untersuchungen zur Lehe von der Gestalt II.* Psychol. Forsch., 4 (1923). Translated as: "Principles of Perceptual Organisation", Readings in Perception, David Beardslee and Michael Wertheimer, Eds., (Princeton, N.J.: 1958), 115-135.

[14] D. Ziou.
Line Detection Using an Optimal IIR Filter Pattern Recognition, Vol. 24, No. 6, pp. 465-478, 1991.

[15] S. W. Zucker, A. Dobbins, L. Iverson.
Two Stages of Curve Detection Suggest Two Styles of Visual Computation. Neural Computation Vol. 1, pp. 68-81, Massachusetts Institute of Technology, 1989.

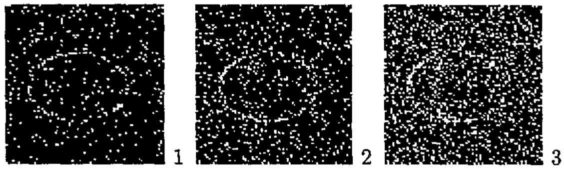


Figure 2:

Initial images: 2.1: 5%, 2.2: 10% et 2.3: 20% of noise on the global images and 40% of noise on the ellipses.

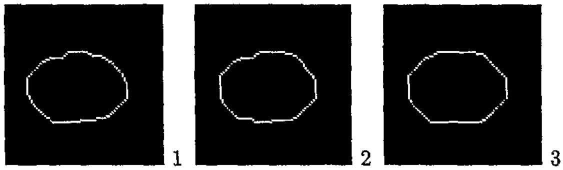


Figure 3:

Results: The images 3.1, 3.2, 3.3 are the groupings found on images 2.1, 2.2, 2.3. For the image 2.3, grey levels of neighboring pixels have been replaced by gaussian directionnal smoothings in the directions of the considered neighbors in the quality functions.

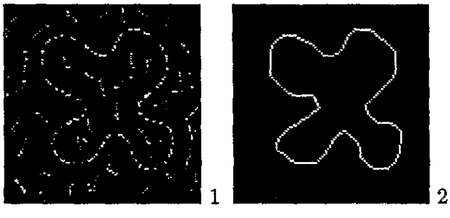


Figure 4:

Image 4.1 is a hand drawing.
Image 4.2 presents the result of grouping of image 4.1.

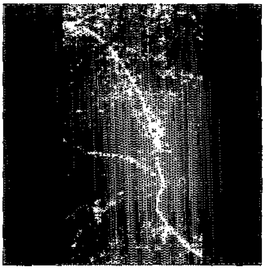
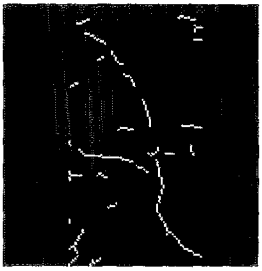

1

2

Figure 5:

Image 5.1 : An satellite image.
Image 5.2, presents a result of line detection on image 5.1, this image is the input to the grouping process.

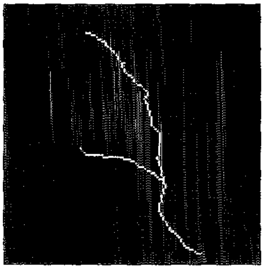

2

Figure 6:

Résults : Image 6.1 presents the result of grouping of image 5.2.
Two principal groupings have been extracted automatically by the "following" algorithm.