Perceptual Organization of thin networks with active contour functions applied to medical and aerial images.

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Abstract

This paper describes a new method of perceptual organization applied to the extraction of thin networks on aerial and medical images. The key point of our approach is to consider perceptual grouping as a problem of optimization. First the quality of a grouping is defined with a class of functions inspired by the energy functions used for active contours optimization (involving curvature, co-circularity, grey levels, and orientation). Such functions can be computed recursively, and optimized from a local to a global level with an algorithm related to dynamic programming. This is followed by a selection procedure which rates and extracts principal groupings. The validity of our approach is presented with synthetic images, aerial and medical data.

Keywords:
Perceptual Organization, Dynamic Programming, Non convex Objects Extraction, Segmentation.

1 Introduction

The detection of thin networks is important for many problems of image analysis. For this class of problems, the lines detected are discontinuous and some of them correspond to no object in reality, because of noise, texture or junctions in the images. This paper proposes a Perceptual Grouping method for the extraction of thin networks, as it is the case with the detection of roads in aerial images or blood vessels in medical images.

Gestalt Psychology [12], or psychology of shape, showed how human vision organizes the representation of the world instead of seeing it in a chaotic way. This approach is based on experimental observations of these grouping phenomena and represents the psychological origin of Perceptual Grouping in Computer Vision.

The aim of Perceptual Grouping [12] [6] [11] [13] [10] is to extract organized structures from visual data and group together primitives coming from common causes. Such groupings structure the visual primitives according to basic geometric relations. These relations can be continuation, symmetry, similarity or object-background separation.

The use of Perceptual Grouping techniques in computer vision is not a recent idea. In 1976, Marr [7] suggested the idea of a "primal sketch" to use both information from contour segmentations and groupings of elements from the image according to primitives such as curves or lines. This idea has never been implemented and Perceptual Grouping has not been really used in Computer Vision before Lowe's work. According to Lowe [6], each grouping has its own statistic feature, representing the probability to be an accidental grouping. This probability is low for salient structures in the scene. Lowe's work showed how Perceptual Grouping could be used to efficiently structure images produced by poorly accurate or biased low-level processing.

Parent and Zucker [9] and also Herault [3] proposed quality functions for perceptual organization using the relation of continuity. These functions used co-circularity, curvature and grey levels. Perceptual organization was accomplished by a global approach of combinatorial optimization or annealing and mean field annealing. An interesting iterative scheme allowing a local to global optimization for some classes of functions was presented by Sha'ashua [10]. Unfortunately, his work did not provide good results on real images, since it was extremely sensitive to noise and didn't take into account global aspects of curves.

In the domain of optimization techniques, models of active contours or Snakes [4] have been developed for the detection of structures containing weak edges. According to these models, the trace of a contour is modified iteratively to minimize an energy function. The energy function is split into independent and yet opposed terms which represent internal and external influences. It also controls the motion of the contour trace. This model, however, shows an important weakness. As the energy function is not convex, there is no direct way to find its minimum. Iterative methods (such as Gradual Non Convexity Algorithm [1]) are available, but they require an initialization close to an optimal solution. Finding this initialization automatically is not easy for most applications, particularly when different objects are present in a scene at the same time.

The method described in this paper falls within the scope of Perceptual Organization with optimization techniques. First in section 2, the quality of a grouping is qualified with 'Snakes like' functions taking into account internal and external influences. Our method is based on a two-stage algorithm which first aggregates the image elements with regard to the quality function. A procedure related to dynamic programming optimizes this quality function from a local to a global level. This gives a new structuring of image primitives, based on smoothed continuation. The optimal groupings are then selected according to their global quality. Section 3 discusses the behaviour of the algorithm and the use of the different parameters. Finally, results on synthetic and real images are presented in section 4. This method is able to recognize large linear structures in noisy images.

2. Perceptual grouping with active contour functions

Low level processing, such as edge segmentation or crest-lines detection applied to complex images describe the content of a scene with a set of image primitives. Due to noise, weak strength of edges, occlusions or textures, this information is spoiled with gaps and false detection. In order to increase the pertinence of this information, we want to fit smooth and continuous curves on these data using quality functions rating the matching. This describes an optimization problem; solutions to this problem are the best matchings between regular curves and the low level primitives. As stated before, a quality function composed of an internal term and an external term is defined, following the same formalism used for the energy functions in models of "snakes". However, at the opposite of snakes, our optimization scheme is done locally. Primitives are organized iteratively together all over the image during the optimization process. The method is described here using pixels as image primitives to group. It can be applied to any image primitive (segments, edge elements, ...) as long as quality terms can be defined.

The main external influence of the image on the solutions is represented by $(\mathcal{G})$, a function of the grey levels of the pixels along the curves in the segmented image after crest lines detection. This matching can be reinforced if the tangents along the solution follows orientations $(\mathcal{O})$ of the low level primitives when available [8].

However the attraction imposed by pixels and local orientations is very important and has to be counter-balanced by shape constraints. Curvature $(\mathcal{C})$ is an elementary way to describe the shape of a curve. In order to obtain stable results, early experiments lead us to add a co-circularity term $(\mathcal{K})$. According to the importance given to the cocircularity term, it is possible to preferentially extract loops or open curves.

The complete quality function is defined as a linear combination of four quality terms.

2.1. Regulation and Image Quality Functions

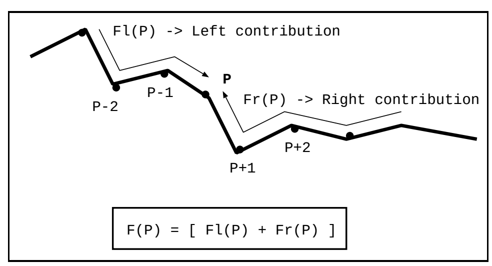

Figure 1. Notations used for a quality term on a dynamic curve during the optimization

The external and internal terms of the quality function follow the same formalism. For a more efficient computation and a global optimization each term can be written in a recursive way as follows (a detailed discussion about the quality terms and algorithms can be found in [5]).

A quality term $\mathcal{F}$ of a curve arriving in a pixel P is defined as the sum of local terms along the trace of the curve entering in and the curve exiting from P, with a factor $0 \leq \rho \leq 1$ representing the attenuation of the quality with distance. If we write the relation as a bi-lateral function of the trace, with a trace $\mathcal{F}_l(P)$ coming in P and a trace $\mathcal{F}_r(P)$ going from P, the quality becomes:

$$\mathcal{F}(P) = (\mathcal{F}_r(P) + \mathcal{F}_l(P)) \tag{1}$$

with :

$$\begin{aligned} \mathcal{F}_l(P) = \quad & \tfrac{1}{2} \cdot Q(P) \\ & + \rho \cdot Q_P(P-1) \\ & + \rho^2 \cdot Q_{P-1}(P-2) + \ldots \end{aligned} \tag{2}$$

and :

$$\begin{aligned} \mathcal{F}_r(P) = \quad & \tfrac{1}{2} \cdot Q(P) \\ & + \rho \cdot Q_P(P+1) \\ & + \rho^2 \cdot Q_{P+1}(P+2) + \ldots \end{aligned} \tag{3}$$

This term written in a recursive way gives, for a distance n starting from P:

$$\mathcal{F}_l{}^{(n)}(P) = Q_P(P) + \rho \cdot \mathcal{F}_l{}^{(n-1)}(P-1) \tag{4}$$

where $Q(P)$ is the local quality term for the pixel P and $Q_P(P-1)$ represents the evaluation of a contribution from the pixel $(P-1)$ viewed from P. Each term of this quality function is representative of a long distance measure of the quality of the curve.

2.2. Optimization of the quality function

A method related to Dynamic Programming [2] [10] is presented here to optimize the quality function iteratively, from a local to a global level.

For each pixel, a connection is defined by a pair of neighboring pixels representing the directions of arrival and departure for a possible curve crossing the pixel. The pair of neighbors giving the best value for the quality function is selected [5]. The recursive expression of the quality functions makes it possible to compute their values with a local part (defined by the local characteristics of the connection) and a global contribution provided by each neighbor. Along the iterations, the importance of individual pixels of impulse noise decreases with regard to pixels included in large structures. The quality of pixels within gaps is increased by influence of neighboring structures.

2.3. Selection of the best solutions

Once the optimization has been performed, the curves are extracted by following the connections from one pixel to another until the chain of pixels crosses its own trace, reaches a boundary of the image or comes to a dead end (for example, when the curve has traced a certain distance without encountering pixels from the segmented image). As the chains are smoothed by the optimization, they are replaced by C-Splines curves for a better description. These splines can be used later to initialize active contours.

The optimization reduces the number of possible curves on the image to a single optimized curve for each possible starting point. Pixels of high local quality are most likely to belong to large structures; they give the starting points of a first selection of good solutions.

This selection is refined with regard to the global quality of the solutions. The global quality of a curve is the sum of local qualities for each of its points. This definition divides the possible solutions into groups of curves with equivalent qualities. It is possible to reduce the number of curves in each group by weighting their quality with an additional factor. This factor is obtained by considering the amount of pixels from the original image encountered by the chain with regard to the amount of pixels followed by filling gaps in this image. A simple thresholding of this weighted function is generally enough to automatically select a set of optimized groupings.

3. Convergence

The quality function can be controlled by two sets of parameters.

The parameters for each term in the final linear combination represent the importance given to these terms in the quality function. They are respectively related to the influence of curvature, co-circularity, strength of crest lines and orientation terms on the shapes of the selected curves. For a high value given to $(\mathcal{G})$, the curves selected will tend to be attracted more by detected pixels. A high influence of $(\mathcal{K})$ will give a better quality to loops instead of open curves.

The second set of parameters is used in the recursive expression of each term. They represent the influence of distant contribution for the term (for example, ρ in (2) and (3)). A value of 0 will reduce the corresponding term to its local value only.

The whole algorithm has a behavior of anisotropic diffusion in the direction of the best connections. In

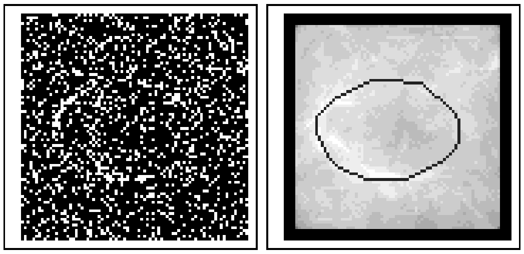

Figure 2. Ellipse 80x80 with %20 of noise - 25 iterations (26 sec / iteration)

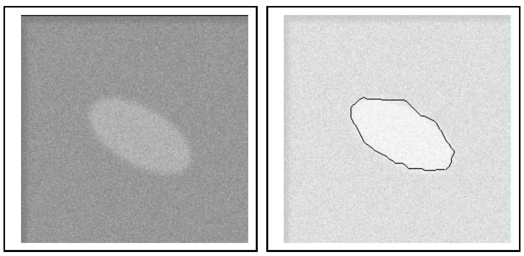

Figure 3. Ellipse 256x256 with Gaussian noise - Segmented Images and Grouping - 10 iterations (5 mins / iteration)

order to fill gaps along the curves of the image, the length of the widest gap gives us the minimum of iterations for the optimization process. We must remember that the optimized curves tend to be smoothed as they receive more global contributions. Thus, a high number of iterations means a loss in the precision of the selected curves. It can be interesting to select the best groupings at various levels of precision as they represent increasingly more global results.

4. Results

All the results in this section have been computed with the same parameters to show the stability of our method.

We have tested our method on Synthetic images (fig 2) with different classes of noise. For both cases, the Signal to Noise ratio (SNR) has been computed as follows :

$$SNR_{dB} \;=\; -10\log\left(\frac{\displaystyle\sum_i\sum_j I(i,j)^2}{\displaystyle\sum_i\sum_j N(i,j)^2}\right)$$

Where $I(i,j)$ represents the image noise free, and $N(i,j)$ the altered image.

In the case of white noise, the image used represents an ellipse where %40 of the pixels have been removed by white noise. %20 of pixels of white noise have then been added to this image (the SNR is $11.4db$). The elliptic shape is still recovered even with high level of noise

In the second situation, the image represents a grey level ellipse where Gaussian noise has been introduced. Edges extraction in this case cannot be performed efficiently by low level edge detection but circular shapes are recovered after applying the perceptual grouping. The SNR is $7.6db$ for this ellipse.

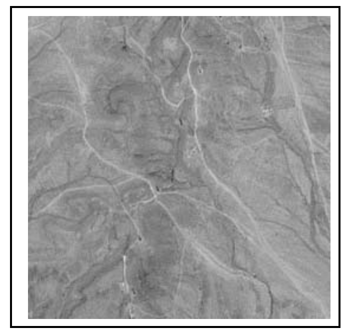

Figure 4. Satellite Picture 256x256 - Original Image

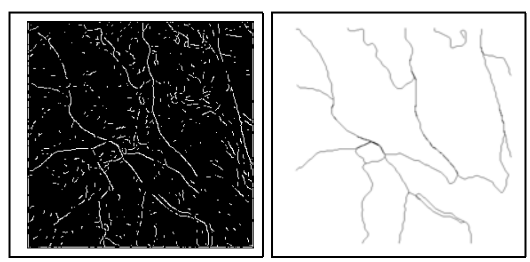

Figure 5. Satellite Picture 256x256 - Segmented image and Final selection of 14 main groupings

Grouping has been applied to crest lines detection on both satellite and medical images. The segmented images in fig 5 and fig 7 show the result of thin network extraction [8]. It is important to remember that the selection algorithm extracts salient solutions according to their quality. This explains the missing groupings one can notice on the results images. It's always possible to obtain more groupings with a lower selection threshold.

More appropriate results to each scene can be obtained by further tuning of these parameters (for

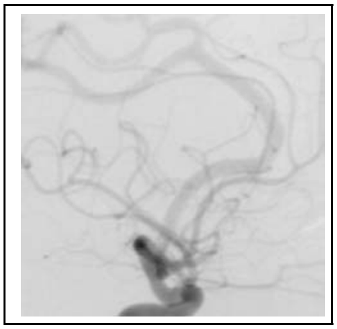

Figure 6. Medical Image 400x400 - Original Image

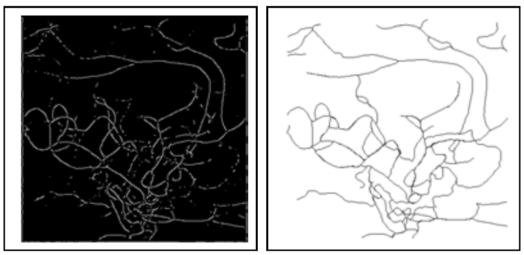

Figure 7. Medical Image 400x400 - Segmented image and Selection of the 50 main groupings

example, increasing the importance of curvature and reducing the importance of grey levels gives better shapes). The extraction of main groupings automatically with no prior knowledge about the shapes produces a first description of the scene and a good initialization for further higher level processing such as model based shape recognition or active contours optimization.

5. Conclusion

We have presented a new optimization technique for Perceptual Organization of thin networks. This technique uses dynamic programming and 'snake like' quality functions. We proposed also a method for the automatic selection of the best curves.

The high quality of the results shows how the method is robust to noise. Our method can be easily applied to real situations with large images such as roads or blood vessels detection. It can be used to initialize a high level interpretation process or to propose optimized solutions to a human expert (such as a physician with medical images).

Possible applications range from closing edges to the initialization of active contours or the extraction of unknown shapes in very noisy images. In the future, we plan to focus on more complex groupings and adapt this method to the extraction of 2D and 3D curves.

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