Snake growing

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1 Introduction

Standard edge detectors usually run in two steps: (i) Detection of edge points; (ii) linking of those points to make a coherent edge feature. Optimal edge detectors were designed ([Can 86]) but this was mainly done on the basis of signal processing aspects and such detectors are often criticized for their failure to detect the most salient edges.

New algorithms based on Active Contour Models have been introduced in [Kas 88]. They provide a global view of edge detection. An active contour model, called a snake, is an elastic curve C which is moving under the influence of the potential energy created by the image gradient. The minima of the snake functional energy are the edges. Using the regularization theory [Pog 85], they are searched for in the restricted class of controlled continuity splines[Ter 86].

The snake functional energy is the sum of two terms: $E = w_1 E_{int} + w_2 E_{ext}$. The Internal energy E_{int} describes features of the curve $C = v(t), E_{int} = \int_C (\alpha|v'|^2 + \beta|v''|^2)$. (Parameters α and β influence the elasticity or stiffness of the curve). The External energy E_{ext} depends on the feature which is searched for in the image (dark lines, white lines, edges, termination of line segments). In edge detection, we use $E_{ext} = \int_C (-|\nabla I(v(t))|)dt$ where I is the image intensity.

The numerical minimization of E is however problematic [Ami 88] because of numerical instability and of numerous parameters in the functional E.

2 Snake growing

Most encountered problems and particularly the instability, are due to the application of the method in bad conditions; for instance, when several parts of the curve have very different behaviors or when several contours (minima of E) lie in the vicinity of the initialization. The snake is influenced by those edges and reaches an apparent equilibrium position. The algorithm is then stopped without reaching a minimum.

2.1 Bootstrapping

Nevertheless, some parts of the curve can be considered as an edge when the whole curve is not. According to an assessment criterion, the snake is then cut into edge subcurves which will be used as bootstrapping edges. So, we develop a method based on the active contour principle using local strategies: a sequence S_i of snakes is built incrementally by successive lengthenings from a small part of an edge, which is either interactively given or inferred by cutting the snake as mentioned above. The sequence S_i is built so as to be always in the neighborhood of a unique contour.

2.2 The basic idea

Let us suppose that we have a curve S_0, even small, which is a contour or is very close to a contour. Then, lengthening the extremities of the curve in the tangent direction gives rise to a curve S_1 which is also close to the contour. Using S_1 as an initialization, the method will converge quickly towards Cl_1 as S_1 is near a local minimum of E. Cl_1 quality is then estimated and the method is iterated.

The Snake growing algorithm can be summarized as:

- *start from a curve S_0 close to a contour,*
- *run the snake algorithm with S_0 as initialization, which yields C_0.*
- *While lengthening is possible, do:(build a sequence C_i of contours whose lengths increase)*
  - *lengthen C_i in the tangent direction to have the initialization curve S_i.*
  - *running the traditional algorithm which converges towards Cl_{i+1}*
  - *assessment of the curve Cl_{i+1} which yields C_{i+1} and the result quality.*

The lengthening of the snake can be interactively selected. It can also be chosen in an adaptative manner in accordance with the snake quality at the previous steps: If the snake quality is good, lengthening can be increased, whereas it is decreased when the estimation quality is bad.

The main advantage of snake growing is that we are at each step in conditions such that the algorithm converges in a satisfying and fast manner because we built an initialization very close to a unique contour. The interest of such a method is obvious when rectilinear contours or contours which present a weak curvature variation have to be detected. This method is also well suited for contour tracking.

2.3 Results and multisnake strategy

Results of snake growing are shown in (Fig.1) on noised and badly contrasted angiographic images. We have chosen to follow an artery using the growing method. Some significant results are exhibited at different steps of the growth.

Automatic Speech Recognition can take advantage of the active contour models. (Fig.2a) shows a cepstrally smoothed spectrogram of the phoneme sequence "soleil". One of the major challenges in acoustic-phonetic decoding is to track the vocal tract resonance frequencies which appear as black lines (maxima of energy) on the spectrogram. (Fig.2) illustrates a **multiple snake growing**. A rectilinear initialization and the resulting curve C after 5 iterations can be seen (Fig.2a). The gradient along this curve is produced in (Fig.2b). The assessment procedure leads to cut the curve C into tree subcurves which are used as initialization of the growth process. The three formant tracks have been correctly caught by this "multisnake" approach as (Fig.2c) shows.

2.4 Discussion

A simple but efficient improvement consists in lengthening the snake in the discrete curvature direction [Lux 85]. This method is particularly efficient when curves whose curvature varies regularly as in smoothed shapes like fingerprint images have to be detected.

Finally, what are the drawbacks of the method ? Our method seems to be more expensive than the traditional algorithm because we have to inverse a matrix at each lengthening (whose size is the snake length), whereas we have a unique matrix to inverse in the traditional method. However, as the sequence S_i is built in such a manner that S_i is close to a contour, the algorithm is more stable and converges more quickly. Nevertheless, it seems difficult to compare the theoretical value of the costs of the two algorithms as they depend on image and on initialization.

3 Conclusion

In this article, we have shown that some local strategies (snake cutting, snake growing, multiple snake) can be used in order to enhance the algorithm efficience, even in noisy surrounding. This kind of method is particularly powerful if we have at disposal knowledge on the searched contours which permit to guide the local strategies. Nevertheless, some problems still remain unsolved in active contour models. The influence of the miscellaneous parameters on the snake behavior and on the accuracy must be clarified. It would be also suitable to be able to merge snake and modeling in order to detect edges whose features are given.

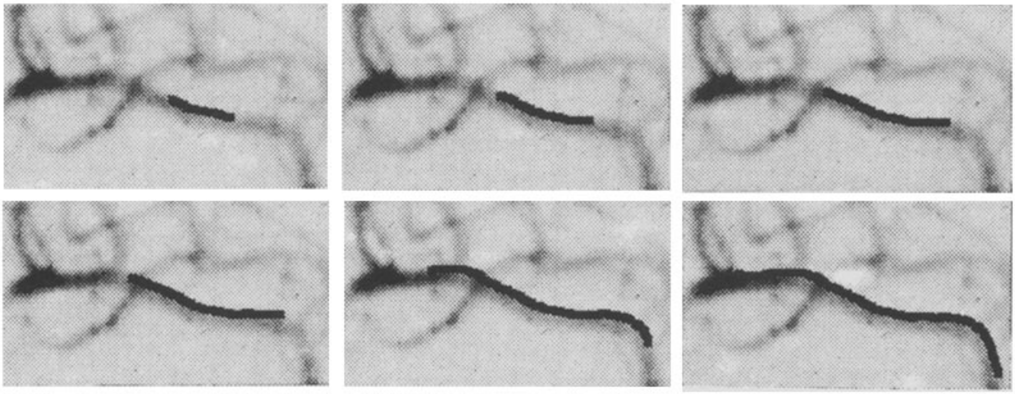

Figure 1: Growing snake on angiographic images.

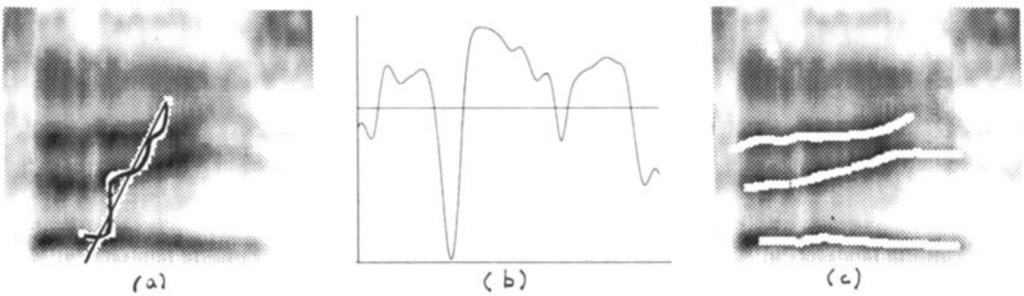

Figure 2: Formant tracking using multiple lengthenings and the gradient curve along the snake.

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