SPEED UP ACTIVE CONTOURS USING LINE SEARCH

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ABSTRACT

The use of active contours in image segmentation constituted a major advance in image processing. However, due to the computational cost, this technique still remains not easily applicable in real time video sequence. Thus, placing ourselves in a step of acceleration of the process, the underlying problem of function minimization is common in other fields of research, like machine learning. We show that the technique of acceleration of convergence, line search, applied in training to algorithms based on the gradient, is adaptable to active contours. The method considered is based on the greedy algorithm which is recognized for its speed. We have shown in the varied images that the addition of the "line search" has notably accelerated convergence, without loss in quality.

KEYWORDS

Active contour, segmentation, image processing, greedy algorithm, line search.

1. INTRODUCTION

Generally, the image processing includes a segmentation phase. The search of contours is often essential in image understanding. The traditional approach uses filters, which makes it possible to obtain some points of the contour. These points need to be linked. This operation uses some interpolations and some choices particularly difficult to decide in noisy images.

By the use of active contours "snakes", the linking is not needed any more. The active contour method was introduced in 1987 by Kass [4]. Contour is modeled using a curve which becomes deformed and, according to the image, fixes itself on the borders of the object. It is the introduction of forces and energies applying at any point of the curve which leads to its deformation. The power of the method comes from the possibility of choosing energies according to the problem which one wants to solve, the image and the objective.

Thus the use of this approach became very current and many publications show their use in very diverse fields; quoting in particular those of biometrics [9], tracking [6] or writing processing [5], etc. Alternatives or improvements are regularly proposed. They often relate to the definition of the involved forces such as balloon force [2] and "Gradient Vector Flow" [13].

In parallel, other methods are developed, such as the level set method [11]. This one makes it possible to better manage the topology of the objects and to reduce the number of parameters of the method. On the other hand, the computing time is increased and it is difficult to use the method in real time applications.

An acceleration of the algorithm has already been proposed in [10] by the use of a taboo list making it possible to avoid the points from going backwards and to avoid the loops. Here, we propose, while remaining within the framework of active contours themselves, to introduce an acceleration of convergence by a method resulting from the machine learning theories.

After having pointed out the general principles of active contours and in particular the modeling which is made in the traditional greedy algorithm [12], we will present the technique of line search then its applications to active contours. We show various examples demonstrating how this process speeds up the convergence time.

2. ACTIVE CONTOUR AND GREEDY ALGORITHM

In the case of the digital image processing, contour is a set of chained points. One can consider that contour is known by the intermediary of a certain number of points which will more or less be numerous according to the required precision. Before specifying the principle of the greedy algorithm, we present the energy functional which it is about the minimizing in order to characterize the contour.

2.1. Energies and Energy Functional

To define the properties of the sought contour, several types of forces are considered. The internal forces manage the intrinsic cohesion of contour, the regularization of the curve, the presence or absence of corners (curve), the regular distribution of the points along the curve in a discrete approach (continuity). The external forces correspond to the data connection, i.e. the image itself. Various elements can be considered, for example the gradient, a light intensity, a color or a property of texture. Context forces can be introduced as the balloon force [2] or other constraints suitable for the application; they make the contour evolve in a particular way. Finally, the evolution of contour is carried out in order to minimize the total energy of contour within the image. One can express this energy by the formula:

$$E(C) = \alpha E_{\text{continuty}} + \beta E_{\text{curvature}} + \gamma E_{\text{gradient}} + \delta E_{\text{balloon}} + \text{etc.}$$

where each energy is weighted by a coefficient which can be local or global .

2.1. Greedy Algorithm Principle

In the case of the greedy algorithm, N points are successively moved one after the other. Energy in each point M of the curve can be expressed by:

$$E(C) = \sum_{j=1}^{p} \mathbf{V} E_j(M)$$

where $\mathbf{V}$ is the vector of weights of the p energies. Total energy for N points of contour is given by:

$$E(C) = \sum_{i=1}^{N} \sum_{j=1}^{p} \mathbf{V} E_j(M_i)$$

It is a question of finding the set of the N points which define the contour.

The greedy algorithm for active contours thus minimizes energy functional in an iterative way. Although the method is not a minimization by gradient of the global functional (which however contains a gradient in one of its energies), it however looks like the minimization problems of an error function which one finds in the machine learning theory.

3. SPEED UP OF ALGORITHMS BASED ON GRADIENT USING LINE SEARCH

Several machine learning methods adopt first order steepest descent technique as learning algorithm, i.e. neural networks [3] [1] or hidden Markov models [8]. Model weights are modified in a direction that correspond to the negative gradient of the error surface.

Considering the error function $f : IR^n \to IR$, supposed convex and twice continuously differentiable, given by the model, the aim algorithm is to minimized $f(x)$ in order to obtain an optimized value $p^* = f'(x^*)$. The necessary and sufficient condition of (local) optimality is given by $\nabla f(x^*) = 0$.

The iterative algorithm computes a sequence of points $\{x^{(0)}, x^{(1)}, \ldots\}$ such that $x^{(k+1)} = x^{(k)} + \Delta x^{(k)}$ where $\Delta x^{(k)} = -\eta \nabla f\left(x^{(k)}\right)$ and $\lim_{k \to \infty} f(x^{(k)}) = p^*$ [7].

Gradient is an extremely local pointer and does not point to global minimum. This hill-climbing search is in a zigzag motion and may move towards a wrong direction, getting stuck in a local minimum. The direction may be spoiled by subsequent directions, leading to slow convergence.

In addition, this search method is sensitive to the parameters such as learning rate and momentum rate. For example, the value of learning rate is critical in the sense that a value too small will make a slow convergence and a value too large will make the search direction jump wildly and never converge. The optimal values of the parameters are difficult to find and often obtained empirically.

The line search technique is a one-dimensional minimization along the gradient direction performed after each gradient calculus in the steepest descent algorithm. Even though this technique is quite costly in number of function evaluations, it reduces the overall time. We summarize the minimization process with the following algorithm:

Given a starting point x and a line search step size $l > 0$

repeat

- determine a descent direction $\Delta x = -\nabla f(x)$
- line search : $t = \underset{0 \le s \le l}{\operatorname{argmin}} f(x + s\Delta x)$
- update : $x \leftarrow x + t\Delta x$

until stopping criterion is satisfied.

4. USING LINE SEARCH WITH ACTIVE CONTOURS

The parallel with active contours is obvious, our f function being the energy function of active contour. In this case, it seems natural, to particularly look at the optimization methods related to the gradient method.

The adaptation of the line search technique consists of: for the point being analyzed, continuing the displacement in the direction given by its preceding displacement. The directions are defined according to the figure below. Direction 9 corresponds to the absence of displacement

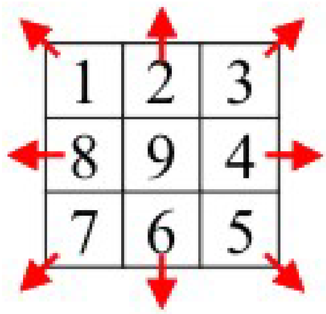

Figure 1 – Displacement directions

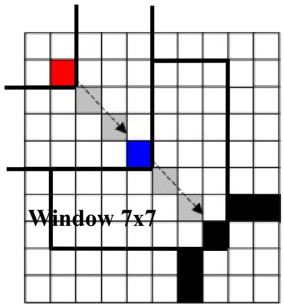

Figure 2 - Without line search

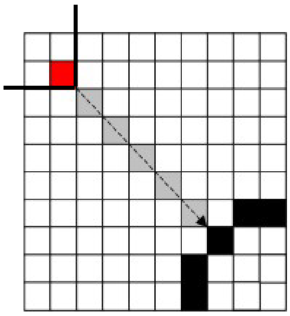

Figure 3 - With line search

On Figure 2, from the initial point, displacement towards contour was carried out in two more iterations. Figure 3 illustrates displacement, using the line search, in only one iteration. After the traditional displacement of a point, the evaluation of energy continues pixel by pixel, in the preceding direction, on L pixels, L being the additional parameter introduced by the line search. In this way, we leave the neighboring window, following the obtained direction. This displacement of a single point in a direction is likely to increase the curve locally and to lose the cohesion of active contour. In order to avoid a too great displacement of a point compared to the others, search in the direction was limited in our examples by ten pixels.

5. RESULTS AND INTERPRETATIONS

The coefficients of intensity, gradient and balloon energies are not modified. Those of curve and continuity must sometimes be adapted. The iteration number is systematically reduced. The neighborhood is realized in a window of 7x7. We tested several types of images and four significant types are retained in this paper. The obtained contours are dotted on the bellow figures. The Figure 4 represents a natural object (a shell) on a very noisy background, with an irregular edge. Figure 5 and Figure 6 are X-Ray images, the first one shows the condyle of the tibio-femoral joint and the second one shows the humeral head from a human shoulder. Figure 7 is constituted of an artificial image (lozenge) with four salient angles. The numerical results of the active contour algorithm with and without speed up technique are compiled in the Table 1.

One can note an improvement of the overall computing time from 5% to 30% compared to the basic method, without loss of visual quality. The iteration number decreases up to 40% according to the images. Each iteration including the line search technique, the gain of time is less.

Image	Line Search	Time	Steps
Broken cowry	w/o	3.7	57
	w/	2.6	35
Condyle	w/o	4.3	76
	w/	3.6	57
Shoulder	w/o	5.4	84
	w/	5.2	74
Lozenge	w/o	4.0	32
	w/	3.0	23

Table 1 - Results with and without line search

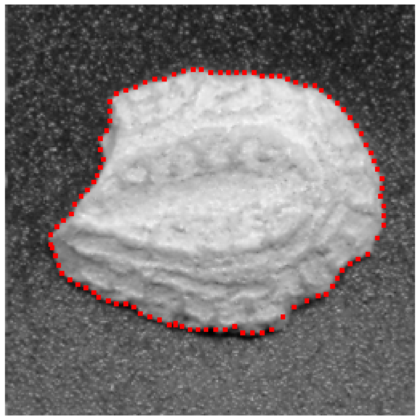

Figure 4 - Broken cowry with line search

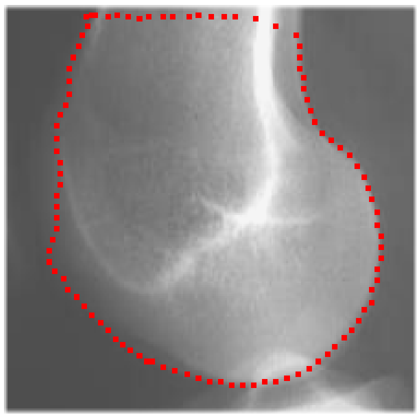

Figure 5 - Condyle with line search

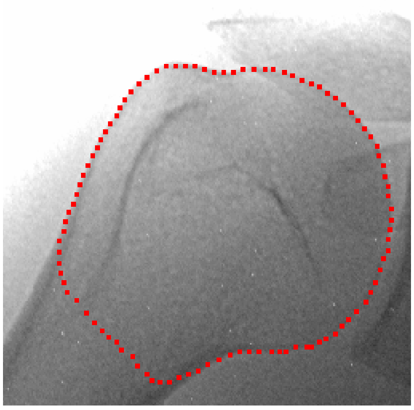

Figure 6 - Humeral head with line search

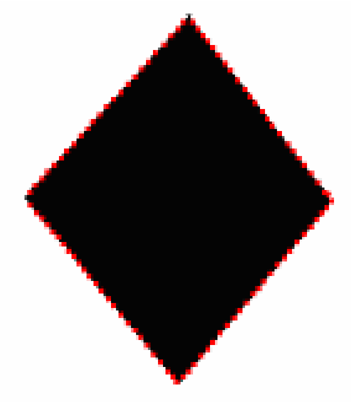

Figure 7 - Lozenge with line search

Table 2 gives results of active contour algorithm without line search but with a window of 10 (21x21). Comparing with Table 1, we can notice that the process duration has strongly increased. We have also remarked that the segmentation quality is slightly inferior.

Image	Time	Steps
Broken cowry	103.6	304
Condyle	25.5	79
Shoulder	57.5	175
Lozenge	5.9	16

Table 2 - Results without line search but with a neighborhood of 10 pixels (window 21x21)

6. CONCLUSION

Firstly we have presented the greedy algorithm principle for active contours and then we have explained the line search. Active contour is essentially an optimization problem. We have shown that by applying a line search to an active contour using a greedy algorithm increases considerably its performance. This new method, particularly simple but efficient, was tested successfully on different kinds of images. This principle is at present used on video sequence processing. We are working on an adaptation for a 3D active contour algorithm.

7. REFERENCES

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