8-11

MVA2007 IAPR Conference on Machine Vision Applications, May 16-18, 2007, Tokyo, JAPAN

A new B-Spline based active contour approach

Sergio Nogueira
System and Transportation Laboratory
UTBM - 90010 Belfort cedex France
Sergio.Nogueira@utbm.fr

Yassine Ruichek
System and Transportation Laboratory
UTBM - 90010 Belfort cedex France
Yassine.Ruichek@utbm.fr

Abstract

This paper proposes a new B-spline based active contour model for extracting areas of interest in an image. The model is governed by original external and internal energies. A self-adaptive technique for energies regulation is used to improve the convergence in terms of quality and rapidity. An adding control point procedure is introduced in order to improve the active contour convergence towards desired image characteristics. Real time applications like object tracking and/or detection could be considered using this new proposed active contour model.

1. Introduction

Edge detection is a traditional step for image analysis. This is achieved generally by using low level filtering operations [1] [2]. These operations, even advanced, do not provide always perfect results due to image noise and edge detector parameters. Furthermore, these classical methods cannot detect globally objects or interesting areas in an image.

For detecting objects or interesting areas, several methods were proposed such as active contours or snakes. Introduced by Kass et al. [3], a snake is a curve that evolves within an image to find edges, generally for object detection or tracking. For example, active contours are often used in medical imaging for organ detection, object detection and tracking in video or 3D reconstruction using stereo vision processes.

This paper deals with a new B-Spline based active contour approach for extracting areas of interest in an image. Using B-Spline curves allow regularity at each point, and, as a consequence, the contour curvature could be estimated. Furthermore, B-Spline curves need only few control points for a good approximation of an object. In order to improve the convergence, a relation between the external and internal energies is introduced thanks to a self-adapting procedure. This is employed to regular both influences of internal and external energies. This concept is based on the fact that the internal energy becomes constant when the number of control points increases.

One of the main problems of active contours is a non convergence to far characteristics. Xu et al. [4] have introduced a new external energy allowing far attraction using the so-called Gradient Vector Flow (GVF) technique. However the GVF requires heavy time computation. In this paper, an original external energy is proposed to get far attraction with fast computation allowing real time application. Combined with an adding control point procedure the model improves the interpolation quality of desired image characteristics.

This paper is organized as follows. Section 2, presents the fundamental properties of our proposed model with the external and internal energies. Section 3, explains the different mechanisms developed for the active contour evolution. Section 4, presents the self-adaptive technique used to accelerate the convergence time. Before concluding, section 5 presents some experimental results.

2. Active contour model

Traditionally an active contour is represented by a C^2 parametric curve, controlled by an internal and an external energies noted E_{int} and E_{ext}. The developed model represents the contour by a cubic B-Spline curve.

2.1. B-Spline curve

A B-Spline curve which is a continuous and derivable is an interesting representation model for an active contour. Indeed, the formulation of the B-Spline curve defines implicitly its regularity. Moreover, a B-Spline curve allows controlling the local bending degree. The used model is a cubic B-Spline Γ defined by n ($n \geq 3$) control points.

2.2. Internal energy

The internal energy controls the elasticity and the bending of the curve. It is defined as:

$$2E_{int}(\Gamma, s) = \int_0^1 \left(\alpha \left| \frac{\delta\Gamma}{\delta s}(s) \right|^2 + \beta \left| \frac{\delta^2\Gamma}{\delta^2 s}(s) \right|^2 \right) \cdot ds \quad (1)$$

Where:

- $\frac{\delta\Gamma}{\delta s}(s)$ denotes the first derivative representing the elasticity value of the curve at the point s;
- $\frac{\delta^2\Gamma}{\delta^2 s}(s)$ denotes the second derivative representing the bending value of the curve at the point s;

In the case of a B-Spline curve, the number of control points influences the stretching and bending of the curve.

Let D be the function $D:\mathbb{R}^2 \to \mathbb{R}$ defining the Euclidian square distance. The proposed active contour model computes the internal energy as follows:

$$E_{int} = \frac{\kappa}{n}\left[\alpha\sum_{i=0}^{n-1} A_i(t) + \beta\sum_{i=0}^{n-1} B_i(t)\right] \quad (2)$$

Where:

- $\alpha, \beta \in [0,1]$, $p \in \mathbb{N}^+$, $t \in [0,1]$
- $A_i(t) = \dfrac{L(S_i(t))}{D(P_i, P_{i+1 \bmod n})}$ (3)
- $B_i(t) = \dfrac{D(P_{i-1 \bmod n}, P_i) + D(P_i, P_{i+1 \bmod n})}{D(P_{i-1 \bmod n}, P_{i+1 \bmod n})}$ (4)
- $L(S_i(t)) = \sum_{j=0}^{p-1} D\left(S_i\left(\dfrac{j}{p}\right), S_{i+1}\left(\dfrac{j+1}{p}\right)\right)$ (5)
- Si(t) is a point situated between the ith and i+1th points of the B-Spline curve and t = à 0,1.

The terms $A_i(t)$ and $B_i(t)$ represent a bending rate. The stretching of the proposed active contour model is controlled implicitly by an adding control point procedure. This allows curve regulation with respect to the desired characteristics in terms of elasticity.
The equation 2 introduces a new parameter κ, which depends on the external energy. It allows a fast convergence of the active contour according to a self-adapting procedure.

2.3. External energy

The external energy is used to attract the snake towards the desired characteristics of the image. Let $P:\mathbb{R}^2 \to \mathbb{R}^2$ be a function giving the local minima corresponding to the desired characteristics of the image. The external energy term is expressed as:

$$E_{ext} = \int_0^1 \gamma P(\Gamma(s)) \cdot ds \quad (6)$$

where gamma is a constant = 0,1

The external energy used in our model is inspired on the concept of the Gradient Vector Flow [4], which allows active contour attraction towards the desired area even if the distance is high. Indeed, our external energy is computed from the distance between the active contour and the desired area.

Considering a B-Spline curve defined by n control points. For each control point P_i of the curve, we search the associate point K_i belonging to the line (D_i), defined by the point P_i as an origin and the normal vector to the curve at P_i and that minimizes the function $f:\mathbb{N}^2 \times \mathbb{N}^2 \to \mathbb{N}$ given by:

$$f(a,b) = D(a,b) + (\Delta_{\max} - \Delta_{xy})^2 \quad (7)$$

where: *(i)* $a = P_i$; *(ii)* $b \in D_i$; *(iii)* $\Delta_{\max}$ the maximum derivation of the image; *(iv)* Δ_{xy} the derivation of the (x, y);

The minimization process finds the best point in terms of influence of both distance and gradient intensity. After the calculation of K_i, a local external energy E^i_{extloc} is computed for the point P_i:

$$E^i_{extloc} = f(K_i, P_i) \quad (8)$$

Finally the external energy is obtained by adding all local external energies:

$$E_{ext} = \frac{\gamma}{\chi}\sum_{i=0}^{n-1} E^i_{extloc} \quad (9)$$

Where X is the initial external energy computed at the initialization of the snake evolution.

3. Curve evolution

Starting from a given initial position, the active contour evolves according to the influence of both internal and external energies:

$$E_{tot}(\Gamma) = E_{\text{int}}(\Gamma) + E_{ext}(\Gamma) \quad (10)$$

3.1. Internal energy influence

Without taking in consideration the external energy, the evolution process produces a growing circular shape of the snake (cf. figure 1).

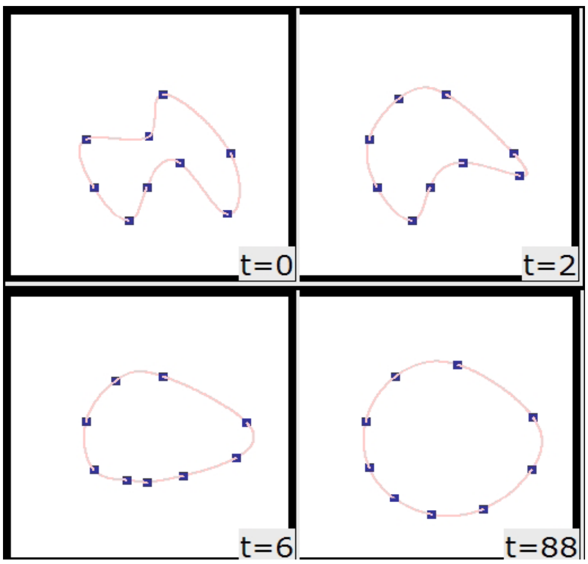

Figure 1. Snake evolution with $E_{ext} = 0$

This property allows getting a circular bounding shape when the external energy is negligible compared to the internal energy.

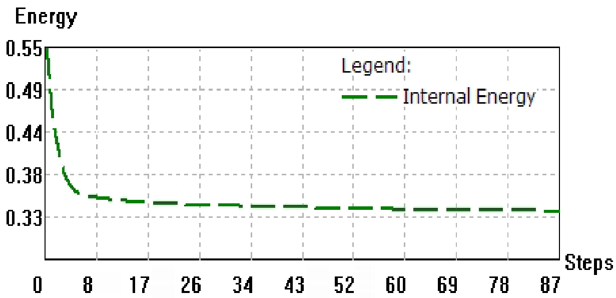

Figure 2. Internal energy evolution

This internal energy improves the snake convergence in terms of quality and rapidity (cf. figure 2). More than 70% of the minimization of E_{int} is achieved on the ten first steps.

3.2. External energy influence

The external energy evolution is characterized by different states. Each state corresponds to a local minimization cycle.

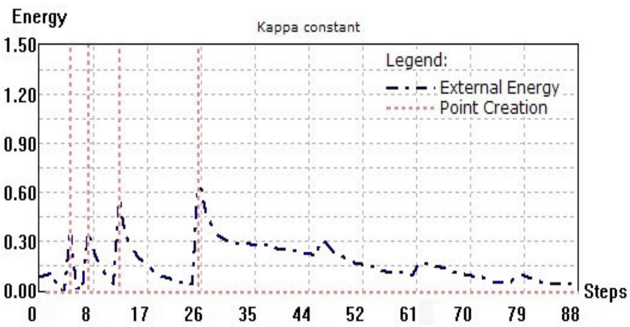

Figure 3. External energy evolution

On figure 3, steps $t=5$, $t=8$, $t=13$, $t=26$ correspond to states in which the external energy becomes stable. At the end of each minimization cycle, some control points are added to launch the minimization process. This is repeated until obtaining a minimum, which depends on how the active contour interpolates the desired characteristics.

Moreover, the figure 3 shows that during the evolution process the distance between two consecutive minimums increases in terms of number of steps.

3.3. The adding control points procedure

The interest of control point adding procedure is to ameliorate the final active contour interpolation shape of the desired image characteristics. On figure 4 (step 12), the two created control points, represented by circles, allow the active contour to reach a better desired concavities.

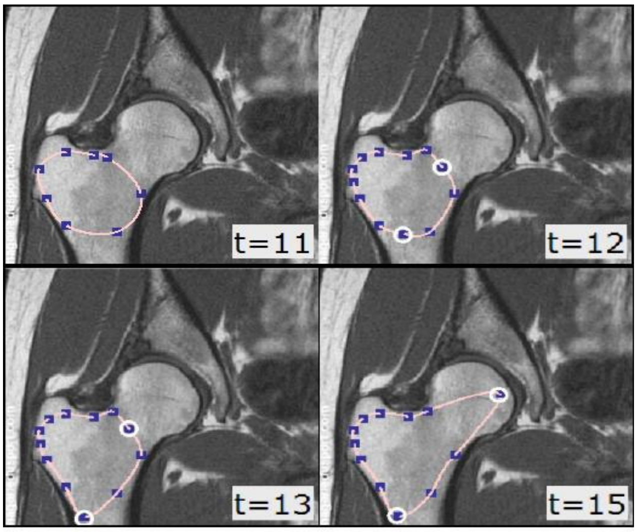

Figure 4. Contribution of the adding control points procedure

This procedure consists in computing for each curve part Si of the B-Spline, the distance between the curve and the desired characteristics. A new control point is created on the middle of Si at the end of each minimization cycle if the curve part is far from desired characteristics.

4. Snake convergence acceleration

To accelerate the convergence of the snake towards the image desired characteristics a self-adaptation of the κ parameter is introduced. This procedure consists in computing the parameter κ proportionally to the external energy. Let λ be a constant, the parameter k is expressed as: $\kappa = \dfrac{E_{ext}}{\lambda}$

Figures 5 and 6 show the interest of the self adapting procedure by comparing the evolution of the internal energy when κ is constant and when κ is self-adapted.

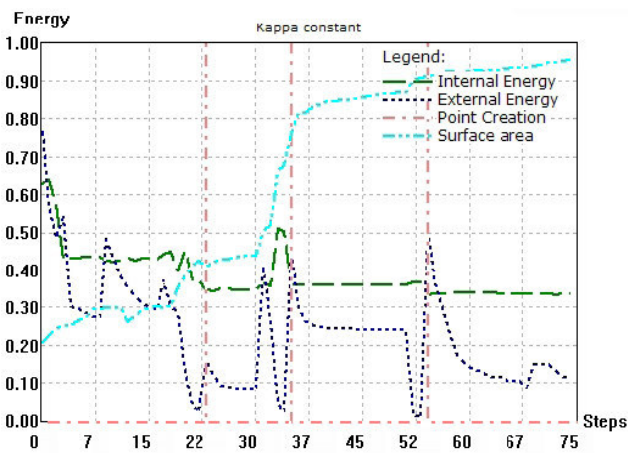

Figure 5. Snake evolution with κ constant

In the case when κ is constant, the internal energy becomes constant after a few steps (cf. figure 5). As a consequence, the influence of the internal energy becomes insignificant. Thus, the snake evolves slowly.

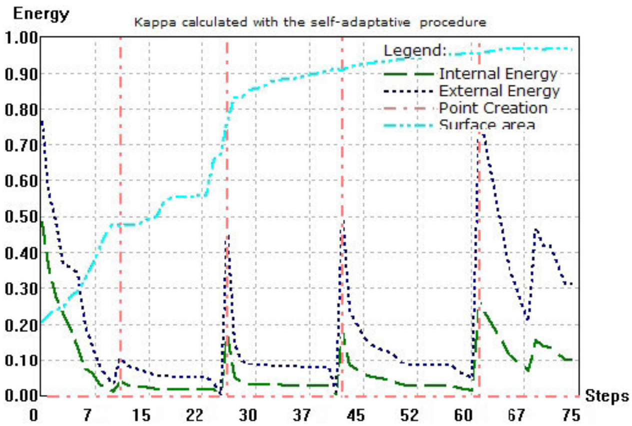

Figure 6. Snake evolution with κ self adapted

The figure 6 illustrates the results obtained from the model with self-adapting procedure. Adapting the parameter κ increases the convergence speed. Indeed, 90% of the surface representing the final contour is reached only after about 37 steps instead of about 52 steps without the self-adapting procedure (cf. figure 5).

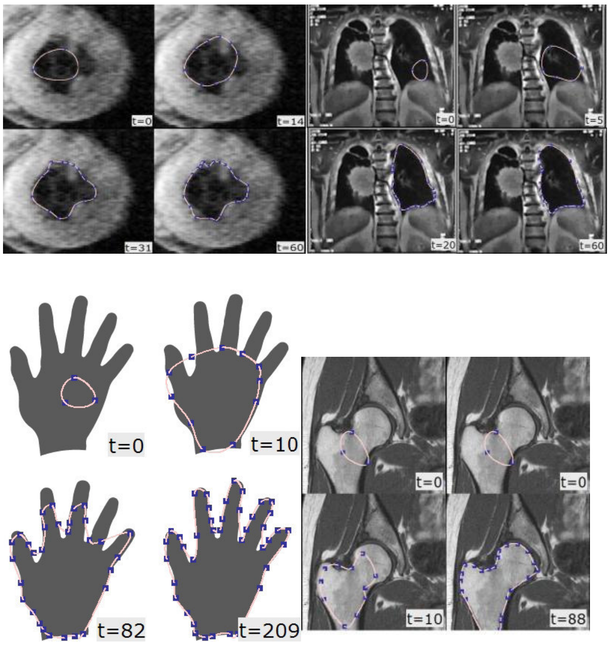

Figure 7. Other results

In addition, the adding control point procedure is involved earlier when the parameter κ is self-adapted. This allows giving the active contour the ability to be attracted earlier towards image characteristics.

Table 1. Computation time

Heart	Lung	Hand	Hip
71 ms	81 ms	656 ms	66 ms

Figure 7 shows other results obtained by our approach applied to different images, without any parameter optimization. Using a Pentium 4 running at 3.0 GHz, the computation time related to the different processed images are shown in table 1.

5. Conclusion

This paper presents new B-Spline based approach for active contour. The proposed model is based on new formulations of internal and external energies with a self-adapting procedure. An adding control point procedure is developed for improving the active contour attraction towards desired image characteristics. The obtained results show the robustness and speediness of the proposed approach.

References

[1] J.F. Canny, “A computational approach to edge detection,” in *IEEE Trans Pattern Analysis and Machine Intelligence*, November 1986, pp. 679–698.

[2] R. Deriche, “Fast algorithms for low-level vision,” *in IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 12, no. 1, 1990.

[3] M. Kass, A. Witkin, and D. Terzopoulos, “Snakes: Active contour models,” *in International Journal of Computer Vision*, 1988, vol. 1, pp. 321–332.

[4] Chenyang Xu and J. L. Prince, “Gradient vector flow: A new external force for snakes,” *in IEEE Proc. Conf. on Comp. Vis. Patt. Recog*. (CVPR’97), 1997, vol. 1, pp. 321–332.