

Cooperative Active Contour Model and Its Application to Remote Sensing

Noriko Matsumoto
Saitama University
Saitama 338-8570, Japan
noriko@ss.ics.saitama-u.ac.jp

Norihiko Yoshida
Saitama University
Saitama 338-8570, Japan
yoshida@ics.saitama-u.ac.jp

Shuji Narazaki
Nagasaki University
Nagasaki 852-8521, Japan
narazaki@cs.cis.nagasaki-u.ac.jp

ABSTRACT

We propose a decentralized cooperative processing applied to the active contour model “Snake”, which applies multiple Snakes to a single region, to improve its detection accuracy. We verify the effectiveness of our proposal in the cases of Multi-Snakes with different parameter sets and Multi-Snakes applied to RGB-decomposed images. We then apply it to multi-spectral remote sensing, and show that Multi-Snakes detected the boundary with enough accuracy.

Categories and Subject Descriptors

I.4.6 [Image Processing and Computer Vision]: Segmentation

Keywords

Boundary Detection, Active Contour Model: Snake, Decentralized Cooperative Processing, Remote Sensing

1. INTRODUCTION

Active contour model “Snake”, proposed by Kass et al., is one of the most popular methods for boundary detection. This paper proposes a decentralized cooperative processing applied to improve Snake. The proposed method applies multiple Snakes to a single region, instead of applying multiple Snakes to multiple regions [1–3], to address inherent problems in Snake. Our proposal has an advantage that it can also be applied to multi-spectral images.

2. ACTIVE CONTOUR MODEL: SNAKE

Snake is a deformable contour $v(s)$ that moves to minimize an energy function E_{snake} . The energy E_{snake} consists of an internal force $E_{int}(v(s))$ and an external force $E_{ext}(v(s))$. Snake is formulated as the minimizing spline of the energy function as follows:

$$E_{snake} = \int \{E_{int}(v(s)) + E_{image}(v(s))\} ds \quad (1)$$

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

SAC'06 April 23-27, 2006, Dijon, France
Copyright 2006 ACM 1-59593-108-2/06/0004 ...\$5.00.

$$E_{int}(v(s)) = (\alpha|v_s(s)|^2 + \beta|v_{ss}(s)|^2) / 2 \quad (2)$$

$$E_{ext}(v(s)) = -\gamma|\nabla I(v(s))|^2 \quad (3)$$

where $v_s(s)$ and $v_{ss}(s)$ denote the first and second derivative of the contour with respect to s , ∇I is image intensity gradient, and each α , β , and γ are weight coefficients.

3. SNAKES AND DECENTRALIZED COOPERATION

The above-mentioned energy function has a complex multi-peak shape, and simple estimation methods are tend to get trapped into a local minimum (or local optimum), and are difficult to reach to the global minimum (or global optimum). Stochastic methods are often used to increase the possibility of reaching the global optimum, however they are highly computationally intensive.

Decentralized cooperative processing is a method to search several possibilities in parallel. It uses several processes (agents) running in parallel. Each agent has its own set of solution candidates (solution space), exchanges intermediate estimations with each other occasionally, and adjusts its estimation process, so as to cooperates to obtain consistency of estimations. Even if any of the agents gets trapped into a local optimum, it will be rescued by the others, so as to reach to the global optimum as a whole. We can expect improvement of estimation qualities in this manner.

We propose to apply several agents in parallel, each of which runs its own Snake, to detect the boundary of a single target object. Each Snake agent does a different estimation using a different energy function or a different image feature. This approach realizes robust estimation against noises and textures, and improve estimation qualities. This paper focuses on two approach in particular as below. Notice that the energy functions and the initial contours are the same in all the Snakes.

(1) Multi-Snakes with different parameter sets

Each Snake agent applies the same energy function with a different set of parameters α , β , and γ to the same image. The shape of the energy function varies according to its parameters. A local minimum in one energy function may not exist in another. Therefore, making the agents cooperate helps to rescue an agent which gets trapped into a local optimum during estimation.

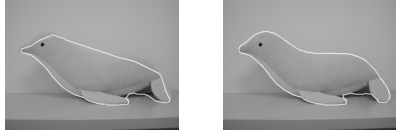
(2) Multi-Snakes applied to some related images

If a given image has only a small intensity gradient between the target region and its background, the original Snake has difficulty to detect the boundary. When the im-



(a) Original Snake (b) Multi-Snakes

Figure 1: Snakes with different parameters



(a) Original Snake (b) Multi-Snakes

Figure 2: Snakes applied to RGB images

age is a colored one, its RGB (Red-Green-Blue) decomposed images are closely-related, but have different features, and any of them may have enough intensity gradient for boundary detection. Assigning these RGB images to three Snakes agents respectively, and making them cooperate, we may detect the boundary of the target more precisely.

4. EXPERIMENTS AND EVALUATIONS

Here we show some results of several experiments using artificial images and real images. The Multi-Snakes uses three agents. The artificial images have 100×100 pixels, and the real images, captured by a digital camera, have 640×480 pixels. All the images have the 256 levels of intensity at each pixel.

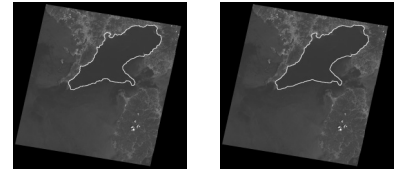
(1) Multi-Snakes with different parameter sets

We ran three original Snakes having a different set of parameters respectively. We also ran Multi-Snakes of the three agents, each of which has the same parameter set as the original Snake respectively. For example, Figure 1 (a) is the result of a Snake (the best of the three) in the former experiment, while (b) is the result of the latter.

It is difficult for the original Snake to determine suitable parameters for the target shape. If the parameter set does not fit for the target shape, Snake fails to detect the accurate boundary even if the target has enough intensity gradient. These experiments show that Multi-Snakes helps to obtain satisfactory results using some sets of parameters, because it relaxes any specific tendency of a single parameter set.

(2) Multi-Snakes applied to RGB-decomposed images

We ran an original Snake to colored images. We also ran Multi-Snakes of the three agents, each of which is applied to the RGB decomposed images. Here we assigned the same set of parameters to both the original Snake and agents employed in the Multi-Snakes. For example, Figure 2 (a) is the result of the former experiment, and (b) is the result of the latter. Even if the original image has poor intensity gradient, Multi-Snakes improved accuracy by applying agents to the RGB decomposed images respectively.



(a) Single-Snake (b) Multi-Snakes

Figure 3: Snakes applied to Multi-spectral images

5. APPLICATION TO MULTI-SPECTRAL REMOTE SENSING

Here we apply this method to a real-world application, remote sensing. Multi-spectral remote sensing uses multiple images of the same area, each of which is of a different single spectrum. Detecting region boundaries is one of the most primary processes in remote sensing. However, as far as we know, there have been no effective methods to estimate boundaries from multi-spectral images, other than image addition or differentiation. We expect that we can address this issue with Multi-Snakes.

We present an experiment result in Figure 3 using three images of single spectra, which were taken from ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) of NASA Jet Propulsion Laboratory, which is 14-channel visible to thermal-infrared sensor, launched as part of the Earth Observing System (EOS) Terra payload.

A region observed in the center of the sea is a polluted region. (a) shows the result of the original Snake. Snake was influenced by local intensity gradients in the sea, and resulted in an unsuccessful contour estimation. To detect this region boundary accurately, information from other images are also required. Therefore, we apply Multi-Snakes of three Snakes agents, each of which handles each single spectrum image. The result is shown in (b).

6. CONCLUDING REMARKS

We proposed an approach to Snake with decentralized cooperative processing to improve the detection accuracy, and verified the effectiveness of our proposal through several experiments. Additionally, we presented application to multi-spectral remote sensing, and showed that Multi-Snakes detected the boundary with enough accuracy. Our current results leave a problem in presetting an initial contour still unsolved. To address this, we are investigating improvements of our approach, including coordination with other approaches.

7. REFERENCES

- [1] T. Wada, Y. Nomura and T. Matsuyama: "Cooperative Distributed Image Segmentation", IPSJ Journal, Vol.36, No.4, pp.879–891, April (1995).
- [2] S. Zhu, A. Yuille: "Region competition: Unifying snakes, region growing, and bayes/MDL for multiband image segmentation", IEEE Trans, Pattern Anal. & Mach Intel., Vol.18, No.9, pp.884–900 (1996).
- [3] Y. Matsuzawa, T. Abe: "Region Extraction Using Competition of Multiple Active Contour Models", IEICE Transactions (D-II), Vol.J83-D-II, No.4, pp.1100–1109, April (2000).