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Improvement of active contour model with decentralized cooperative processing and its application to remote sensing

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Abstract. Active Contour Model, "Snake", is one of the most popular boundary detection methods. Its principle is an energy-minimizing spline for estimating the closest contour of a target object in an image gradually from an initial contour. However, this method has difficulty to determine an initial contour and parameters, and it cannot detect the target boundary precisely when the target image does not have clear edges or uniform feature. In this paper, we propose decentralized cooperative processing applied to Snake, which applied multiple Snakes to a single region, to improve its detection accuracy. The multiple Snakes run in coorperation with each other so as to increase the possibility of reaching the global optimum, and improve the estimation qualities. We verify the effectiveness of our proposal, in particular Multi-Snakes with different parameter sets, and Multi-Snakes applied to RGB-decomposed images, through the experiments using artificial images and real images. We then apply it to multi-spectral remote sensing, and show that our proposal detected the boundary with enough accuracy.

1. Introduction

Accurate boundary detection in an image is one of the most important problems, yet difficult to solve, in image recognition. Active contour model "Snake", proposed by Kass et al. [1], is one of the most popular methods for boundary detection. The principle of Snake is an energy-minimizing spline for estimating the closest contour of a target object in an image. This energy spline consists of forces emanated from both the shape of the Snake and the image. By using parameters specifying the effects of these forces, Snake can detect various shapes. This method has been studied intensively because it has a simple principle, it makes stabilizing extraction easy, and it enable us to embed features of the target object into an extraction process.

However, Snake still has some problems. It is difficult to determine parameters suitable for a target shape. Snake is also prone to noises in an image. In order to address these issues, various improvements have been proposed, such as a method using a sample contour for initial (a priori) estimation [2], and a method using a statistical model [3]. These proposals are effective only when the target shape and the image do not differ from the anticipated model.

Moreover, Snake can detect the target boundary precisely only if the object has clear edges, and the image has uniform features in the object region and the background region respectively. Otherwise, the detection result becomes worse because the estimation process lapses into a local minimum instead of the global minimum. In order to address this issue, various methods have been proposed, such as a method dividing an image into several uniform regions beforehand [4], a method applying two Snakes simultaneously to the target region and the background region [6], and a method making some Snakes to compete or cooperate [5,7]. However, they require strict positioning of many sample points for the initial contour(s).

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This paper proposes decentralized cooperative processing applied to improve the active contour model, Snake. The proposed method, Multi-Snake, applies multiple Snakes to a single region, instead of applying multiple Snakes to multiple regions as mentioned above. The multiple Snakes run in coorperation with each other so as to increase the possibility of reaching the global optimum, and improve the estimation qualities. Our proposal has an advantage that it does not conflict with other established or proposed methods. Instead, ours can be cooperated with others so as to improve estimation qualities even more.

We verify the effectiveness of our proposal, in particular Multi-Snakes with different parameter sets, and Multi-Snakes applied to RGB-decomposed images, by the experiments using artificial images and real images. We then apply it to multi-spectral remote sensing, and show that our proposal detected boundaries with enough accuracy.

This paper is organized as follows. Section 2 summarizes Snake, and Section 3 describes the principle of decentralized cooperative processing. In Section 4, we propose Snake with decentralized cooperative processing. After showing effectiveness of our proposal by some experiments using artificial images and real images in Section 5, we present its application to boundary detection in multi-spectral remote sensing in Section 6. Section 7 evaluates performances of our proposal, and Section 8 contains some concluding remarks.

2. Active contour model, Snake

Snake is a deformable contour

$$v(s) = [x(s), y(s)], s \in [0,1] \tag{1}$$

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 $E_{ext}(v(s))$. $E_{int}(v(s))$ indicates elasticity and smoothness of the contour, and $E_{ext}(v(s))$ is derived from the image along the contour $v(s)$ so as to be attracted to a certain edge. Snake is formulated as minimizing a spline of the energy function as follows:

$$E_{\mathrm{snake}} = \int \{E_{int}(v(s)) + E_{ext}(v(s))\} ds \tag{2}$$

$$E_{int}(v(s)) = (\alpha|v_s(s)|^2 + \beta|v_{ss}(s)|^2) \ / \ 2 \tag{3}$$

$$E_{ext}(v(s)) = -\gamma|\nabla I(v(s))|^2 \tag{4}$$

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. It means the value of this energy function gets smaller, if the shape of the closed contour is more circular, if the circumference length is shorter, or if the intensity gradient is larger. However, this tendency depends on the parameter settings.

In general, Snake transforms the contour to minimize E_{snake} from an initial closed contour provided by a user, and searches the target boundary. Snake calculates the changes of the function value at each point, namely each control point, on the closed contour, and moves the control point to a direction whose energy gradient is the steepest. Thus, Snake searches the target boundary sequentially from the initial contour, so that it tends to be influenced extremely by the initial contour. Snake also has a drawback of strong dependence to the local information, which is intensity gradient along the closed contour, as expressed in Eq. (4). Hence, the detection accuracy becomes worse when the target image consists of complicated features.

3. Decentralized cooperative processing

The above-mentioned energy function has a complex multi-peak shape. Such simple estimation methods as “hill climbing” and “steepest descent methods” have tendency to get trapped into a local minimum (or local optimum), and are difficult to reach to the global minimum (or global optimum). This degrades severely estimation qualities of boundary detection in Snake.

There are various general techniques proposed to increase the possibility of reaching the global optimum, and improve the estimation qualities. Among them, such stochastic methods as “simulated annealing” and “genetic algorithms” are often used.

Another kind of technique is Decentralized Cooperative Processing that is a variant of multi-point search which searches several possibilities in parallel. This is vigorously researched in the area of Distributed Artificial Intelligence [8]. We already did some theoretical investigation for decentralized cooperative processing, and for example, we applied this technique to Multi-target Motion Analysis, and succeeded to achieve the same estimation quality ten time faster compared to simulated annealing [9–11].

Decentralized cooperative processing uses several processes (agents), each of which can perform searching by itself, and make them run 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 cooperate to obtain consistency of estimations. Even if any of the agents gets trapped into a local optimum, it will be rescued by the others, in order to reach the global optimum as a whole. We can expect reduction of incorrect convergence, and improvement of estimation qualities in this manner.

This exchange and cooperation mechanism resembles exchange and cooperation of intermediate models in distributed interpretation, and cooperation of the intermediate plans in distributed planning.

4. Snakes and decentralized cooperation

Based on the above-mentioned background, we propose improvement of the detection accuracy of Snake by applying the decentralized cooperative processing.

The original Snake applies a single energy function with a set of parameters to estimate the boundary of a single target object. As mentioned above, this method is prone to noises and complex textures in the image, and parameter mismatch. These cause degradation of estimation qualities.

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. It exchanges its intermediate contour estimation with each other periodically, and adjust its own contour estimation. This approach follows exactly the general framework described above, and realizes robust estimation against noises and textures, and improves estimation qualities.

Each agent runs Snake, and can detect boundaries by itself. An agent could run any proposed improvement of Snake. Our proposal does not conflict with other proposals. On the contrary, it can cooperate with others so as to improve estimation qualities even more. Our proposal complements decentralized cooperative Snakes by Wada et al. [5] in the sense that it applies multiple Snakes not to multiple regions but to a single region.

There are four assortments to coordinate multiple Snakes, or Multi-Snake, as below. The last one was proposed using decentralized cooperative processing [5], MDL [6], or competition [7]. For the third one, we are investigating adopting a model of target boundary to a detection process, and now we are performing some experiments. Hence, this paper focuses on the first two in particular.

- Snakes with different parameter sets for E_{snake};
- Snakes with different (but closely related) images;
- Snakes with different energy functions;
- Snakes with different initial contours.

Namely, Snakes with different parameter sets or different images exhibit different estimation characteristics, and the proposal is to make them cooperate. Their details are described below. Notice that both of the energy functions and the initial contours are the same in all the Snakes.

4.1. 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 minimum during estimation.

For example, most real images include noises in intensity gradient which cause local minima, and degrade estimation qualities in the single Snake. The original Snake has difficulty to fix appropriate parameters to cope with this problem. In our approach, we can cope with it by assigning different γ to each Snake.

4.2. 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, because of the definition of the energy function.

When the image 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 Snake agents respectively, and making them cooperate, we can detect the boundary of the target more precisely. The shape of the energy function varies according to its image data, and any of them may have enough gradient.

"Color Snakes" [12] is an extension of Snakes for vector-valued (color) images. The author mentioned two possible approaches: the first is to process each plane separately, and then integrate the results to obtain one unique segmentation; the second is to integrate the vector information from the very beginning, and deform a unique curve, directly obtaining a unique segmentation. Then the author pointed out some problems in the first: (1) boundaries (objects) may be defined by the combination of the different planes; (2) while different planes are highly correlated, this correlation is not used in the segmentation process; (3) the step of curve integration is not trivial. Consequently, the author adopted the second approach.

We adopt the first approach on the contrary, and introduce a mechanism to integrate results at each iteration. This solves all the three problems quoted above. Our approach has an advantage that the processing of the vector-valued images can be seamlessly integrated with processing by multiple agents of different parameters or functions in a single framework of decentralized cooperation.

The overall detection procedure common to both (1) and (2) above is as follows:

Set an initial contour (by the user);
Repeat for each control point on the contour;
 Find a candidate of new control point in each agent;
 Exchange information and find the optimal candidate;
 Fix a new control point in all agents;
until converged.

When the gradient (the first derivative) of the energy function calculated in a certain agent gets small, this means the agent gets near to a local minimum or the global minimum. However, if the gradient in another agent still keeps large at the same control point, it is supposed that the agent is not at the global minimum but at a local minimum.

Accordingly, each agent exchanges with each other the direction which gives the largest energy gradient among its eight-neighbors, and follows the direction which gives the largest gradient among the values from all the agents. This scheme is shown in Fig. 1. This exchange takes place at every moment when the agents move control points.

Our proposal has possibility bringing the vibration of control points, although it is often observed even in the original Snake. In order to prevent the vibration, we have brought in the preventive measure which detects the vibration and restricts the movement of the vibrating control point. The vibration is considered as movement between the same coordinate a number of times, so the process of detecting the vibration finds such kind of movement. If a certain control point is in the vibration, the restricting function locks it on the current coordinate temporarily.

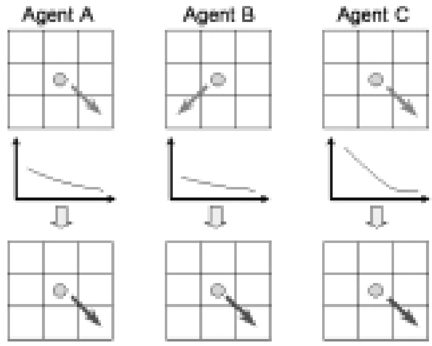


Fig. 1. Decision of new control points.

5. Experiments and evaluations

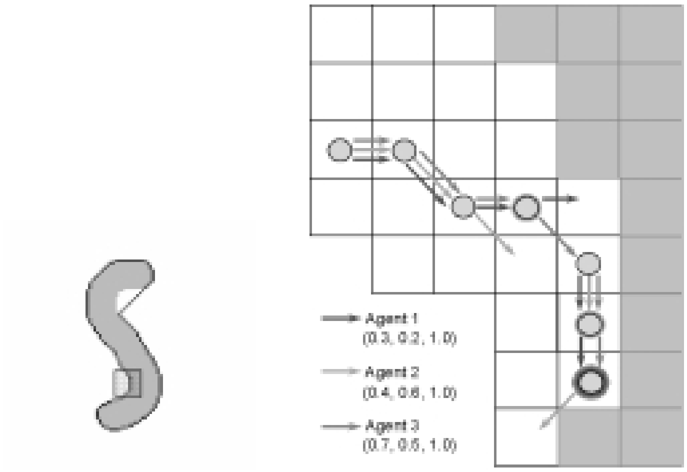
In order to verify the effectiveness of our proposal, we performed several experiments about two approaches mentioned above. In these experiments, agents are simulated on a single process, instead of implemented as multiple processes.

We compared results of the original single Snake and results of our cooperative multi-Snakes. The Multi-Snakes uses three agents. Convergence calculation is done using Amini's dynamic programming [13]. Experiments used both some artificial images and real images. The artificial images have 100×100 pixels, and the real images have 640×480 pixels. All the images have the 256 levels of intensity at each pixel.

Before showing some experiment results, we show how our proposal moves control points, namely how it elects an agent in the boundary detection process of Fig. 5. Figure 2 shows a tracking result of a certain control point in the region surrounded by the blue square in (a). Arrows represent the new control point candidate of each agent, and we can track the choice of agents by following these arrows. Each agent estimates a new control point candidate based on its solution space respectively, exchanges its energy gradient with other agents, and follows an agent whose energy gradient is the largest, then it moves to the same coordinate as other agents. The circle surrounding a control point represents the case that an agent decides to stay on the same coordinate but not to move to a new coordinate. Repeating this process, Multi-Snakes realizes the boundary detection.

5.1. Multi-Snakes with different parameter sets

We ran three original Snakes having a different set of parameters respectively. We also ran Multi-Snake of



(a) Target region (b) Candidates of agents

Fig. 2. The track of Multi-Snake.

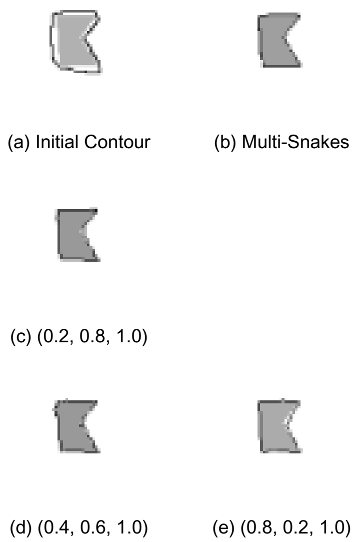


Fig. 3. Experiment with different parameter sets (1): case 5.

the three agents, each of which has the same parameter set as the original Snake respectively.

First, we performed experiments using eight artificial images. All the images have enough intensity gradient between the target region and background. They are divided into two groups: images of simple shape targets which are easy to detect, and images of complex shape targets which are difficult to detect.

Table 1 summarizes results of these experiments. A, B, and C denote the original Snakes, and A+B+C indicates the Multi-Snakes of cooperating A, B, and C. The values in the table are the accuracy of estimation, which is evaluated as $R_{\mathrm{area}} = |N(Y) - N(X)| \,/\, N(X) \times 100$, where X is the true region of the target, Y is the region detected by Snake, and $N(Z)$ is the number of pixels in a region Z. Consequently, the smaller R_{area} implies the higher accuracy.

Experiments with simple shapes show that both the original Snake and Multi-Snakes exhibit enough accuracies. Experiments with complex shapes show that original Snake fail to exhibit enough accuracies, and Multi-Snakes outperforms.

Multi-Snakes became worse than a single Snake in the case 6 of complex shapes. Its target shape has a deep concave region as shown in Fig. 4. Original Snake cannot show enough accuracies in concave region because its energy potential pulls a contour like a rubber band. Even Multi-Snakes with different parameters cannot improve this drawback sufficiently if a concave region is too deep. For example, Fig. 3 shows the case 5, and Fig. 5 shows the case 7 in Table 1. In each figure, (a) shows the initial contour in a solid black curve, and (c), (d), and (e) are the results of the original Snakes with (α, β, γ) shown under the pictures. (b) presents the result of Multi-Snakes employing agents whose parameters are the same as in (c), (d), and (e).

Figure 5 has two concave regions, both of which are shallower than the one in the case 6. This shape is also too complex for original Snake. Multi-Snakes cannot detect the perfect target boundary, however, it can improve the detection accuracy. Looking at the two concave regions, the result of Multi-Snakes is actually a combination of the best estimation of all three agents.

Next, Fig. 6 shows the experiment results using real images. The meanings of (a)–(e) follow the above-

Table 1
Estimation errors in experiments with different parameter sets

Case		Original Snake			Multi-Snakes
	A	B	C	A+B+C	
simple	1	0.00	0.00	0.00	0.00
	2	0.17	0.17	0.17	0.17
	3	0.27	0.14	0.14	0.14
	4	0.00	0.00	0.00	0.00
simple ave.			0.09		0.08
complex	5	11.68	7.48	12.31	2.02
	6	3.50	3.55	4.97	3.87
	7	9.49	25.75	9.30	4.70
	8	6.64	5.60	6.88	4.43
complex ave.			8.93		3.76
all ave.			4.51		1.93

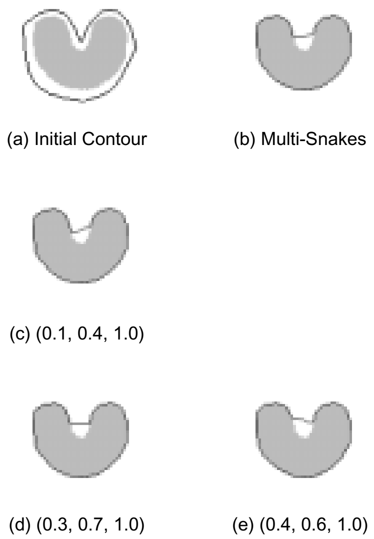


Fig. 4. Experiment with different parameter sets (2): case 6.

mentioned Fig. 3. The improvement of accuracy by Multi-Snakes is observed the same as in the artificial images shown above.

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.

5.2. *Multi-Snakes applied to RGB decomposed images*

We applied 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.

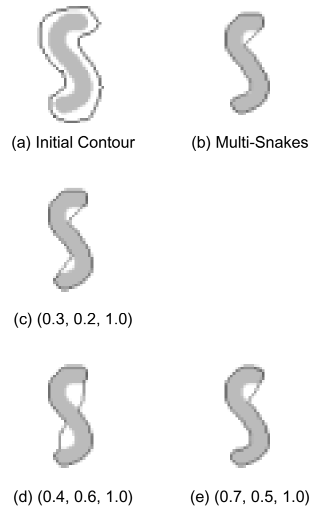


Fig. 5. Experiment with different parameter sets (3): case 7.

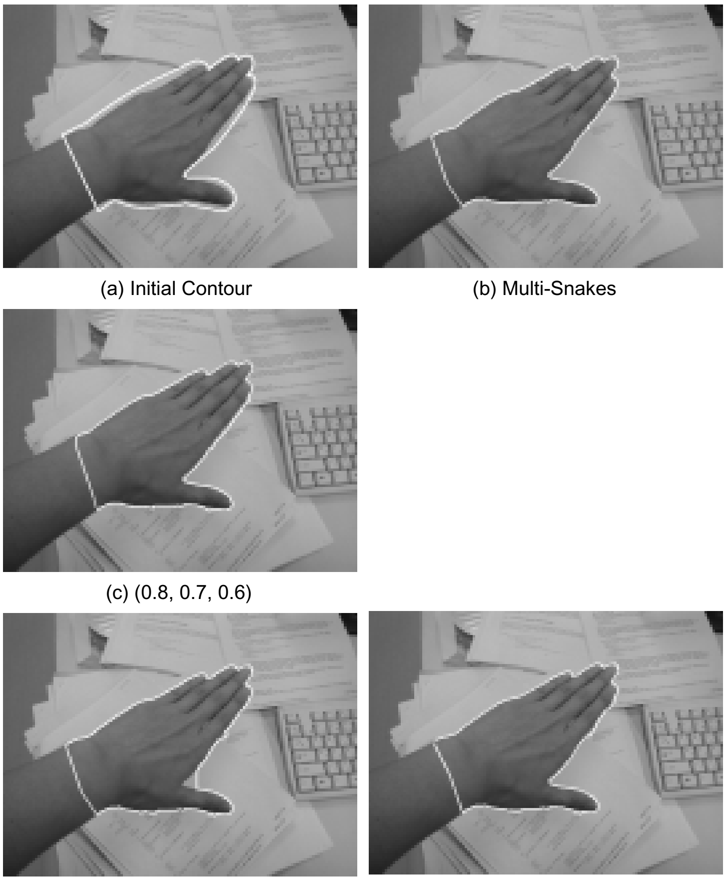
First, we performed experiments using three artificial images. We used an image (Fig. 3), and arranged it so that its intensity gradient is very small between the target region and background. We used the same initial contour and the same parameter set as the ones which brought the best result in the previous experiment.

For example, Fig. 7 shows one of the results. Color arrangement of this is shown in Table 2. (a) is the result of the original Snake applied to the colored image, and (b) is the result of Multi-Snakes whose agents were applied to RGB decomposed images respectively. In the other experiments, we observed the similar results as well.

Next, Fig. 8 shows the result using real images. (a) presents the intensity of the image by color gradation. This image has a boundary of the poor intensity gradient, in particular, at the back of the doll. (b) is the initial contour in white, (c) is the result of the original Snake, and (d) is the result of Multi-Snakes employing agents whose parameters are the same as in (c). Even if the original image has poor intensity gradient, Multi-Snakes improved accuracy by applying agents to the RGB decomposed images respectively.

6. Application to boundary detection in multi-spectral remote sensing

As described in the previous sections, the decentralized cooperative Snakes, or Multi-Snakes, can be well

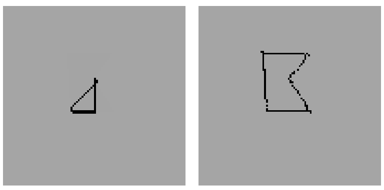


(a) Initial Contour (b) Multi-Snakes

(c) (0.8, 0.7, 0.6)

(d) (0.6, 0.8, 0.8) (e) (0.7, 0.6, 0.7)

Fig. 6. Experiment with different parameter sets (3): real image.



(a) Original Snake (b) Multi-Snakes

Fig. 7. Experiment with RGB images (1).

applied to RGB decomposed color images to improve estimation accuracy for boundary detection. Each Snake agent handles an image of the single spectrum, and cooperates with each other. Here we apply this method to a real-world application, remote sensing.

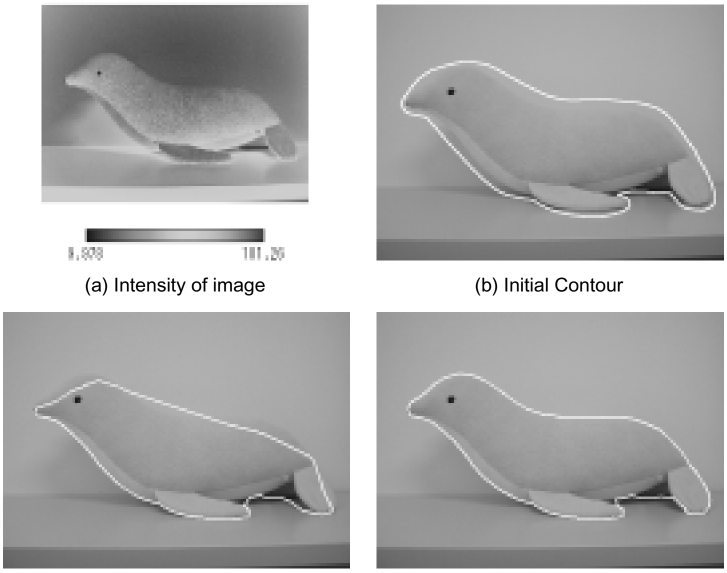
Remote sensing is to obtain information of the ground or sea, analyzing images taken from planes or satellites. Multi-spectral remote sensing uses multiple images of the same area, each of which is of a different single spectrum.

Table 2
Intensity of the experiment image

	I (intensity value)	R	G	B
background	164.93	51	255	0
target	164.63	153	153	255

Detecting region boundaries, for example, warm and cold area in the sea, forests, and crop fields, is one of the most primary processes in remote sensing. The original Snake has been widely used for boundary detection from a single image. 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 with some figures, Fig. 9(a)–(c) which show three images of single spectra (Tachibana Bay, Nagasaki, Japan on May 14, 2000). They were taken from ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) of NASA Jet Propulsion Laboratory, which is 14-channel



(a) Intensity of image (b) Initial Contour

(c) (0.8, 0.7, 1.2) (d) Multi-Snakes

Fig. 8. Experiment with RGB images (2): real image.

sensor (visible to thermal-infrared,) launched as part of the Earth Observing System (EOS) Terra payload. Each spectrum is 0.5 μm (green), 0.6 μm (red), and 0.7 μm (infrared), respectively.

Using these images, we show a comparison of three detection results: a result of original Snake applied to a single spectrum image, a result of original Snake applied to a color composite image which is a classical approach, and a result of our proposal. Color composite image is shown as (d), we assigned green to 0.5 μm, blue to 0.6 μm and red to 0.7 μm, artificially. In the experiments of our proposal, we employed three agents, and they were applied to a different spectrum image respectively.

The target region is “the region of uniform water in the bay”. The boundary of this region can be observed apparently the most in the green image (a), where the outside of this boundary is a polluted region. The boundary is tend to be straight and smooth. (e) shows the result of the original Snake applied to the 0.5 μm image (a). Snake was influenced by local intensity gradients in the sea region, and resulted in an unsuccessful contour estimation. To detect this region boundary accurately, both information from the 0.6 μm and 0.7 μm images which have less noise by such as reflection, are also required. (f) shows the result of the original Snake applied to the color composite image. This image is obtained by mapping each spectrum to red, green, and blue, respectively, of an RGB image, so that we can analyze comprehensively the feature of the same target region observed in each spectrum. However, this process also synthesizes noise at the same time, so that this result of the original Snake could not exhibit enough accuracies. Next, we applied Multi-Snakes of three Snake agents, each of which handles each single spectrum image. The result is shown in Fig. 9(g).

Figure 10 shows shows some enlarged parts out of Fig. 9. (a) shows the target boundary as a hand-written white line, and this is an edge between the region of uniform water in the bay and the polluted region in the sea, which is blurred by noises. (b) is the result of an original Snake applied to 0.5 μm image, (c) is the result of an original Snake applied to the color composite image, and (d) is the result of Multi-Snakes. In both the cases using a single spectrum image (b) and the color composite image (c), the original Snake could not exhibit enough accuracies because of the noises in the sea region. Multi-Snakes detected the desired boundary without being affected by the noises, because of its cooperation that agents avoided the local optima of energy function by exchanging information which include less noises between agents.

(e) is a coast detected using original Snake applied to a single spectrum image, (f) is the result of the original Snake applied to the color composite image and (g) is the same part using Multi-Snakes. Snake tends to be smoothed, rounded and attracted to the point which has a bigger intensity gradient, so original Snake was

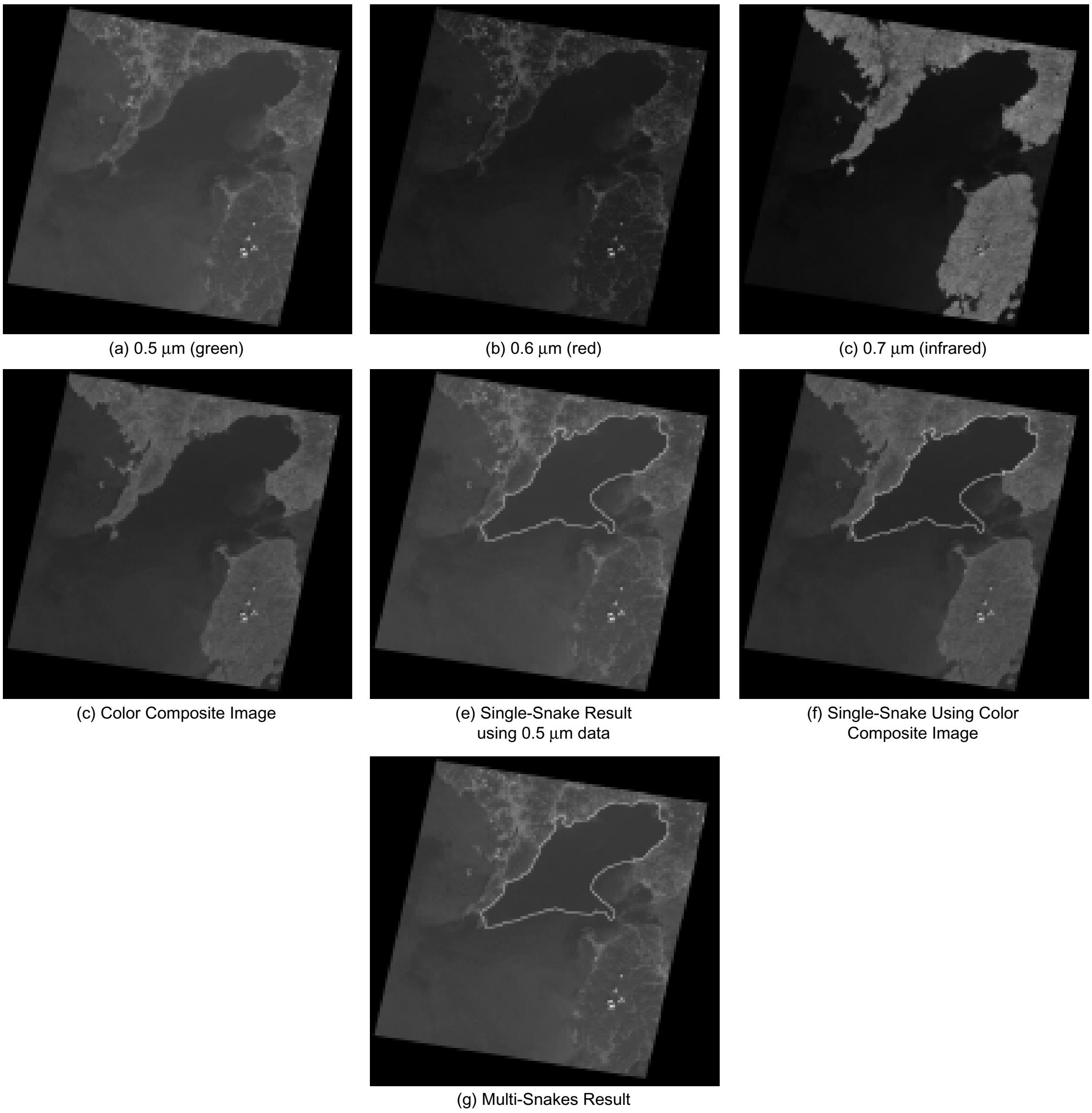


Fig. 9. Experiment with multi-spectral remote-sensing images (1).

attracted to intrude the cost in both cases of (e) and (f). On the contrary, Multi-Snakes detected the desired coast.

The original Snake which is applied to a spectrum image got trapped into the local optima of noises around the target boundary. In the detection process using the color composite image, it can realize the integrative boundary detection with the synthesis of multiple spectra. However the synthesis also includes noises, which the reason why it could not exhibit enough accuracies. On the contrary, Multi-snakes detected the desired boundary because of the comprehensive analysis brought from sharing information about all spectra respectively.

However, this experiment reveals that it is difficult to apply this method well to very fine structures of coast line. This must be improved by integrating other proposed methods.

7. Performance evaluation

Table 3 shows the execution time of the experiment programs, and the number of loops in the above-

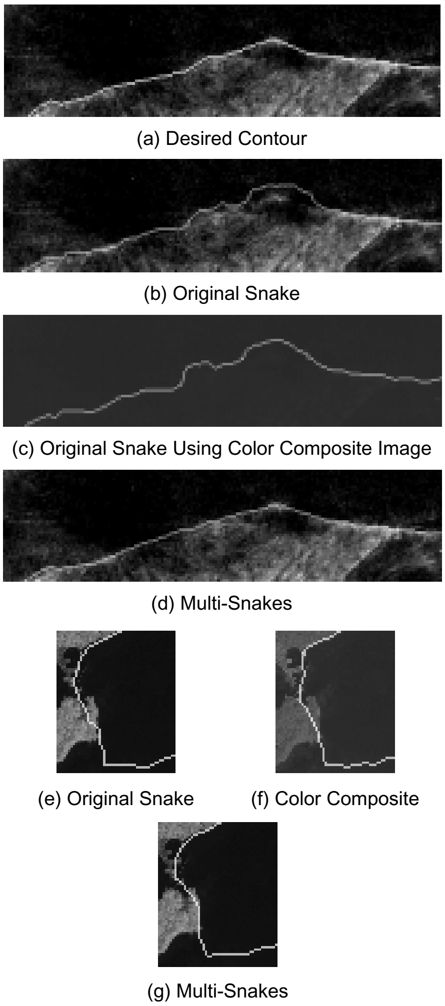


Fig. 10. Experiment with multi-spectral remote-sensing images (2): Enlarged.

mentioned experiments on the artificial image, the real images, and the remote sensing images. In this table, "Snake" denotes the original Snake, and "Multi" denotes Multi-Snakes. The CPU used in these experiments is Celeron 2.50 GHz.

The time/loop, namely the execution time of one loop, of Multi-Snakes is almost the same in the case 1, and about three times longer in the case 2 compared to the original Snake. It is due to implementation of the simulation system. In the case 1, all the computation of $|v_s(s)|^2$, $|v_{ss}(s)|^2$, and $|\nabla I(v(s))|^2$ in Eqs (3) and (4) are actually shared among the agents, and using them, each agent computes its E_{snake} applying a different parameter set of α, β, and γ respectively. On the contrary, in the case 2, the computation of $|v_s(s)|^2$, $|v_{ss}(s)|^2$, and $|\nabla I(v(s))|^2$ are done separately in each agent, which

Table 3
Performances of experiments

		Time(sec)	Loop	time/loop
case 1: different parameters				
Art (Fig. 3)	(0.2,0.8,1.0)	0.0154	16	0.000963
	(0.4,0.6,1.0)	0.0154	13	0.00118
	(0.8,0.2,1.0)	0.0466	47	0.00101
	Multi	0.0532	12	0.00127
Art (Fig. 5)	(0.3,0.2,1.0)	0.0468	31	0.0015
	(0.4,0.6,1.0)	0.047	28	0.00168
	(0.7,0.5,1.0)	0.131	87	0.00151
	Multi	0.047	31	0.00152
Real (Fig. 6)	(0.8,0.7,0.6)	3.07	324	0.00947
	(0.6,0.9,0.8)	2.82	295	0.00955
	(0.7,0.6,0.7)	3.33	347	0.00959
	Multi	3.68	334	0.0110
case 2: decomposed images				
Art (Fig. 7)	Snake	0.0406	42	0.000967
	Multi	0.0602	22	0.00301
Real (Fig. 8)	Snake	18.2	1998	0.00910
	Multi	38.0	1395	0.0273
ASTER (Fig. 9)	Snake	15.0	803	0.0187
	Multi	33.8	657	0.0514

makes the execution time three times longer on a single processor.

We cannot simply compare the number of loops because it depends heavily on the process of convergence. However, we observed reduction of the number of loops using Multi-Snakes. When the information of intensity gradient is not enough, the influence of internal force gets large. This force makes the contour to be more circular and smaller, so the original Snake transformed to an undesired contour. On the contrary, Multi-Snakes detected the desired boundary using the information derived from each spectrum image, so the number of loops become smaller than that of an original Snake.

8. Conclusion

We proposed an approach to Snake with decentralized cooperative processing to improve the detection accuracy. We verified the effectiveness of our proposal through several experiments, namely, Multi-Snakes with different parameter sets and Multi-Snakes applied to a set of single spectrum images.

Multi-Snakes with different parameter sets solves the difficulty to determine a suitable parameter set for a target boundary, and Multi-Snakes applied to a set of single spectrum images can detect a target boundary in a given image whose intensity gradient is too small. These experiments show that our proposal improves the possibility to obtain the global optimum. Additionally, we presented application to multi-spectral remote sensing, and showed that Multi-Snakes detected the boundary with enough accuracy.

Our current work leave a problem in presetting an initial contour still unsolved. This problem imposes users some trial-and-errors to obtain high estimation accuracy. To address this, we are investigating improvements of our approach, including coordination with other approaches.

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