# Layered Cooperation of Macro Agents and Micro Agents in Cooperative Active Contour Model

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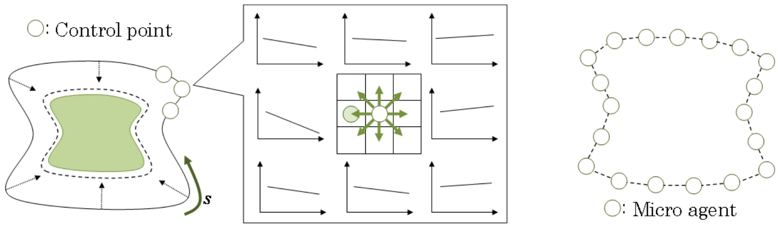
**Abstract.** We have proposed *Multi-Snake*, which realizes boundary detection in image recognition with the layered cooperation of micro agents and macro agents. Cooperation in a set of micro agents constructs the behavior of a macro agent, and cooperation of the micro agents are integrated to cooperation of the macro agents. This mechanism makes the application more dynamic and flexible. Our previous proposals dealt with cooperation between some macro agents of the same kind. This paper focuses on the cooperation of macro agents of different kinds: sensor-based macro agents and model-based macro agents. We show that our proposal makes estimation improved and more robust. We verify the effectiveness of our proposal through some experiments using artificial images and real images.

## 1 Introduction

Image recognition and feature extraction are still difficult to solve although there have been many proposals applying various techniques including agents techniques. Accurate boundary detection in an image is one of the most important problems in image recognition, however it is also still difficult.

One of the most popular boundary detectors is Active Contour Model "Snake", proposed by Kass et al. [1]. The principle of Snake is an energy-minimizing spline for estimating the closest contour of a target object in an image gradually from an initial contour. This principle can be considered as a boundary detector realized by cooperation in an aggregate of many micro agents, that is, the contour is a single macro agent which consists of a set of micro agents. There have been some proposals concerned with cooperation of macro agents. In this paper, we discuss layered cooperation which integrates the cooperation of the micro agents, who construct a macro agent, to the cooperation of the macro agents. In this way, we can produce the macro cooperation from the micro cooperation. The layered cooperation make this application more dynamic and flexible.

We have proposed Multi-Snake, the improvement of Snake in this manner. This proposal so far has been concerned with cooperation of macro agents of the same kind, and we verified its effectiveness [2–4]. Our another paper [5] presented some preliminary idea on cooperation of macro agents of different kinds, namely, sensor-based macro agents and model-based macro agents. In




(a) Operation at each control point

(b) Macro agent composed of micro agents

**Fig. 1.** Principle of Snake

this paper, we investigate some fundamental aspects on cooperation of macro agents of different kinds based on cooperation of micro agents.

## 2 Active Contour Model, Snake

Snake is a deformable contour $v(s) = [x(s), y(s)], s \in [0, 1]$ 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:

$$E_{snake} = \int \{E_{int}(v(s)) + E_{ext}(v(s))\}ds \tag{1}$$

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

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

where $v_s(s)$ and $v_{ss}(s)$ denote the first and second derivative of the contour with respect to $s$, $\nabla I$ is image intensity gradient, and each $\alpha$, $\beta$, and $\gamma$ 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 as shown in Figure. 1(a). Therefore, it can be considered that each control point is a micro agent and, the contour is a single macro agent as an aggregate of the micro agents (Figure. 1(b)).

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 the formula (3). Hence, the detection accuracy becomes worse when the target image consists of complicated features. In order to address this kind of issue, various methods have been proposed using some macro agents distributed in space, such as a method dividing an image into several uniform regions beforehand [6], a method applying two Snakes simultaneously to the target region and the background region [7], and a method making some Snakes compete or cooperate [8, 9]. However, they require strict positioning of many sample points for the initial contour(s).

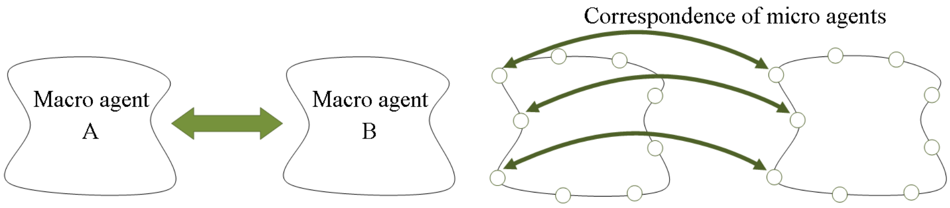
## 3 Multi-Snake

The original Snake has some drawbacks of its strong dependence on the parameters, the target features and the target image as mentioned above. In order to address these drawbacks, we have proposed *Multi-Snake*, an improvement of Snake by applying the agent technique, with the layered cooperation mechanism [2–4]. This method uses several macro agents in parallel, each of which runs its own Snake, to detect the boundary of a single target object. Each macro agent does a different estimation being based on different solution space, using different parameters, or being applied to closely-related different images. This cooperation of macro agents are realized by the cooperation of micro agents, that is, *Multi-Snake* has two layers as shown in Figure 2 (a) and (b). Some micro agents, which are located at the same control point on the contour, exchange their intermediate contour estimation with each other periodically, and adjust their own contour estimations. This approach realizes robust estimation against noises and textures, and improves estimation qualities.

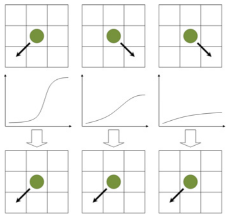
When the gradient (the first derivative) of the energy function calculated in a certain macro agent gets small, this means the agent gets near to a local minimum or the global minimum. However, if the gradient in another agent still keeps large at the same control point, it is supposed that the agent is not at the global minimum but at a local minimum. Accordingly, in the micro agent layer, each corresponding micro 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 micro agents. This scheme is shown in Figure 2(c). This exchange takes place at every moment when the micro agents move control points. This cooperation of the micro agents layer realizes the cooperation of the macro agents layer.

## 4 Model-based Snake

As mentioned above, *Multi-Snake* has two layers as shown in Figure 2 (a) and (b), and we have verified its effectiveness, but using macro agents of the same kind so far. To improve the estimation quality even more, we discuss cooperation of macro agents of different kinds [5], namely sensor-based macro agents and model-based macro agents. First, we introduce model-based Snake.




(a) In the macro layer (b) In the micro layer

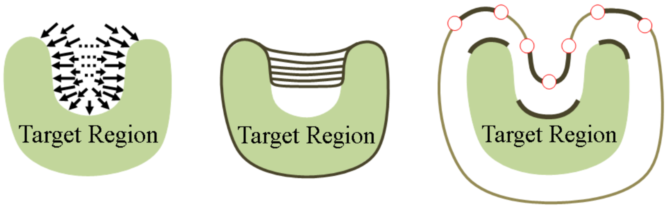


(c) Decision of new control points

**Fig. 2.** Cooperation mechanism of Multi-Snake

Snake is prone to complex shapes, concave boundaries, and pointed boundaries. In particular, the concave boundaries cannot be detected by adjusting its parameters only, and this problem is still left as a big problem. This is caused by the energy potential as shown in Figure 3 (a), in which arrows express the forces to attract Snake to the target. A user must place an initial contour on the region very close to the target concave region so as to make Snake converge to the concave. Once Snake escapes from the energy potential to attract to the concave, it is inevitable to transform into a straight line as shown in Figure 3 (b). This is the core of the problem. In order to solve this kind of problem, we have an observation that the initial contour placed by a user implies (or can be given easily) some information of the target shape.

There have been some methods using a model as information of the target shape; for example, a proposal determines $E_{int}$ which is suitable for the target shape by presenting the prototype beforehand [10, 11], or another proposal determines a range of acceptable shape divergence by estimating the average shape of target and the unevenness of shape [12–16]. In particular, Matsuzawa [16] adopts the symbolized information, such as "corner", "curve", "segment", and "arc", which is obtained from the shape of initial contour. Based on this symbolized information, this method assigns these shape information to each control point of Snake respectively, and makes control of Snake reflect the shape knowledge of target region. This approach has an advantage of its ability which can include the model with the process of boundary detection without giving up Snake's advantages of the ability of general-purposeness and handiness. Based on this approach, we have considered modeling the fragment shapes of the initial contour to bring in the model to the control of Snake. Matsuzawa's symbolization




(a) Potential (b) Snake convergence (c) Our idea

**Fig. 3.** Around a concave boundary region

cannot describe the fine features, although control Snake by the target model acquired from the shape information in an initial contour. Hence, we use the curvature at each region more concretely.

Our model-based Snake, which we call *Curvature Snake*, selects the feature points from the initial contour, and models the curvature among the feature points. We bring in this curvature to Snake as a model.

*Curvature Snake* uses the energy function as follows:

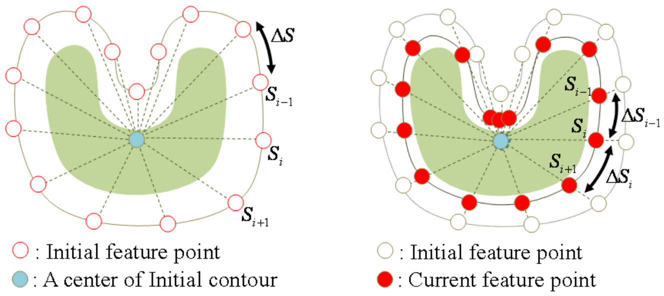
$$E_{CS} = \int \{E_{int}(v(s)) + E_{ext}(v(s)) + E_{model}(v(s))\} ds \tag{4}$$

$$E_{model} = \delta |E^0_{curv} - E_{curv}| \tag{5}$$

where $E^0_{curv}$ is the initial curvature calculated on a feature point on the initial contour. These initial feature points are placed on the contour at an equal interval ($\Delta s$) as shown in Figure 4 (a). $E_{curv}$ is the current curvature calculated on a feature point on the current contour at each moment. When the current curvature approximates to the model (the initial curvature), $E_{model}$ gets smaller, therefore Curvature Snake can hold the information from the initial contour.

When we notice the details of transformation of Snake, namely the movement of the control points, there is a case that the control points move along the contour. Therefore, this method needs a mechanism corresponding between a model and the current feature point. At each moment, the current feature point is selected from the control point which is on the base-line. *Curvature Snake* calculates $E_{CS}$ (Form.(4)) only when it is on the feature points. When on the other control points, it calculates the original energy function only. There would be various kinds of base-lines, such as the normals in the initial contour, or the line drawn from a gravity center of the initial contour; here we use the latter, because the feature points gather to concave region according to the convergence as shown in Figure 4 (b).

Now, we describe the calculation of curvature from the feature points. The initial feature points is determined as the points dividing the initial contour at an equal interval $\Delta s$ (Figure 4(a)). From these feature points, the calculation uses the first and second derivative as follows:




(a) Initial feature points and base-lines (b) Current feature points

**Fig. 4.** Principle of *Curvature Snake*

$$\frac{dx_i}{ds} \approx \frac{x_{i+1} - x_{i-1}}{2\Delta s} \qquad \frac{d^2x_i}{ds2} \approx \frac{x_{i+1} - 2x_i + x_{i-1}}{\Delta s2}$$

$$\frac{dy_i}{ds} \approx \frac{y_{i+2} - y_{i-1}}{2\Delta s} \qquad \frac{d^2y_i}{ds2} \approx \frac{y_{i+1} - 2y_i + y_{i-1}}{\Delta s2}$$

where $\frac{dx_i}{ds}$ and $\frac{d^2x_i}{ds^2}$ is called $x_s$, $x_{ss}$, the curvature $k_i$ of feature point $S_i$ is defined as follows:

$$k_i = \frac{y_{ss}x_s - x_{ss}y_s}{(x_s^2 + y_s^2)^{\frac{3}{2}}}$$

On the contrary, the current feature point in the detection process at time $t$ cannot use the same equation as mentioned above, because its interval between the feature points is different respectively (Fig. 4(b)). However, the current curvature need not be completely exact, so that it is approximated during the detection process as follows:

$$\frac{dx_i}{ds} \approx \frac{x_{i+1} - x_{i-1}}{\Delta s_{i-1} + \Delta s_i} \qquad \frac{d^2x_i}{ds2} \approx \frac{x_{i+1} - 2x_i + x_{i-1}}{\Delta s_{i-1} \cdot \Delta s_i}$$

$$\frac{dy_i}{ds} \approx \frac{y_{i+2} - y_{i-1}}{\Delta s_{i-1} + \Delta s_i} \qquad \frac{d^2y_i}{ds2} \approx \frac{y_{i+1} - 2y_i + y_{i-1}}{\Delta s_{i-1} \cdot \Delta s_i}$$

where $\Delta s_i$ is the arc between the feature point $S_i$ and $S_{i+1}$ as shown in Fig. 4(b).

## 5 Curvature Multi-Snake

Now we propose the layered cooperation of sensor-based agents and model-based agents, namely, the original Snake agents and *Curvature Snake* agents. We call this cooperation "*Curvature Multi-Snake* (*CMS*)". *Multi-Snake* has two layers as shown in Figure 2 (a) and (b), and *CMS* also has two layers.

In *CMS*, the original Snake cooperates with *Curvature Snake* at the feature points, because there are cases that the only *Curvature Snake* cannot keep the smoothness of the contour depending heavily on the shape of initial contour at each feature point.

At a feature point which crosses the base-line, each micro agents 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 micro agents in the same manner of *Multi-Snake*. The differences between *Multi-Snake* and *CMS* is only the occasion of when the cooperation is happen. *CMS* makes agent cooperate only at the feature points.

The overall detection procedure of *CMS* is as follows:

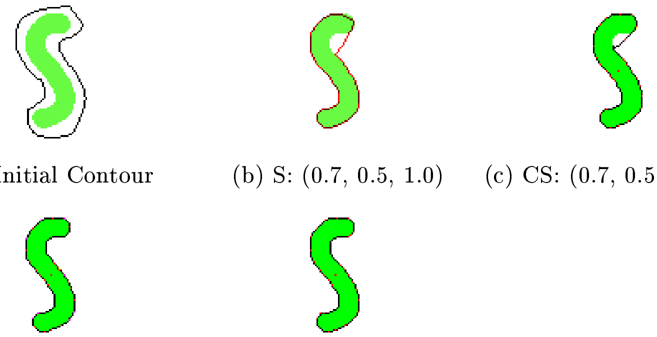
```
Set an initial contour (by user)
Find the center of initial contour
Divide the initial contour at an equal interval (Δs)
Repeat for each control point on the contour
  If the control point is on the base-line
    Make Original Snake cooperate with Curvature Snake
  Else
    Find a new control point using the original energy
Until converged.
```

Preserving the model at each feature point by *Curvature Snake*, *CMS* is able to overcome the difficulty of boundary detection without giving up Snake's advantage of the smooth result contour by this cooperation performed only on the feature points.

## 6 Experiments

In order to verify the effectiveness of our proposal, we performed several experiments about *Curvature Snake* and *CMS*. In these experiments, we used artificial images ($100 \times 100$ pixels) and real images ($640 \times 480$ pixels) which have 256 levels of intensity for each color at each pixel.

First, we show results of experiments using some artificial images. Figure 5 (a) presents the initial contour in a solid black curve, (b) is the results of the original Snake with $(\alpha, \beta, \gamma)$ shown under the pictures, and (c) is the results of the single *Curvature Snake* with $(\alpha, \beta, \gamma, \delta)$. In this experiment, *Curvature Snake* does not cooperate with the original Snake on the feature points, but uses the energy function $E_{CM}$ only. On other control points, it performs the same as the original Snake. The purpose of this is to verify the effectiveness of the model force $E_{model}$ added to the energy function. In this picture, the result of boundary detection are shown in a solid black curve, the red pixels on each contour are the feature points. The number of feature points is thirty. As shown in (c), *Curvature Snake* failed to exhibit enough accuracies even with preserving shape. This is caused by the lack of desired effects of the model, namely the lack of appropriate correspondence between initial feature points and the current feature points. This result means that the single *Curvature Snake* has the target



(a) Initial Contour (b) S: (0.7, 0.5, 1.0) (c) CS: (0.7, 0.5, 1.0, 1.0)

(d) S: (0.7, 0.5, 1.0) + CS: (0.0, 0.0, 0.0, 1.0) (e) S: (0.7, 0.5, 1.0) + CS: (0.7, 0.5, 1.0, 1.0)

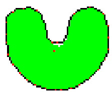
**Fig. 5.** The results of Curvature Snake and CMS

shape which cannot coordinate with the feature points as desired by a user. It depends on the target shape or the movement of control points.

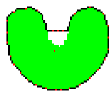
Then, we show how *CMS* influences the result accuracy when it makes original Snake of parameters $(\alpha, \beta, \gamma)$ cooperate with *Curvature Snake* of parameters $(0.0, 0.0, 0.0, \delta)$. In this case, *Curvature Snake* is not affected by $E_{int}$ and $E_{ext}$, so that the micro agents of original Snake cooperate with a model-based micro agent which depends on $E_{model}$ only at each feature point. (d) is the result of this case, and the parameters are shown under the pictures. This result shows the improvement of the accuracy of detection boundary. Additionally, we performed the experiments in which original Snake is cooperated with *Curvature Snake* with parameters $(\alpha, \beta, \gamma, \delta)$ instead of $(0.0, 0.0, 0.0, \delta)$. (e) exhibits enough accuracies as well as the experiments as in (d). In these experiments of *CMS*, we checked which agents were chosen, and confirmed tendency to choose the original Snake agent as its convergence progressed.

In the experiments of the single *Curvature Snake* (Figure 5 (c)), the process of boundary detection is performed with parameters $(\alpha, \beta, \gamma, \delta)$, so that Snake is certainly influenced by the model force. On the contrary, the process in *CMS* ((d),(e)) chooses better suited agents according to both the contour shape and the image force at each moment. This means that *CMS* adjusts the influence of the model-based agents dynamically, consequently reduces the undesired transformation of the contour in concave regions, and at the same time can detect more smooth boundaries than the single *Curvature Snake*.

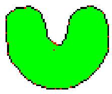
However, *CMS* cannot exhibit enough accuracy with all parameter sets. There are some cases which failed to detect the concave region, for example we show that results in Figure 6 (a) and (b). *CMS* can improve its accuracies by increasing macro agents of original Snake whose parameter sets are different respectively. We performed the experiments of *CMS* employing three agents, namely two sensor-based agents and one model-based agent. Figure 6 (c) show the result, and



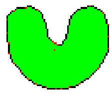
(a) S: (0.1, 0.4, 1.0)
+ CS: (0.1, 0.4, 1.0, 1.0)



(b) S: (0.3, 0.7, 1.0)
+ CS: (0.3, 0.7, 1.0, 1.0)



(c) S: (0.1, 0.4, 1.0)
+ S: (0.3, 0.7, 1.0)
+ CS: (0.4, 0.6, 1.0, 1.0)



(d) S: (0.3, 0.7, 1.0)
+ CS: (0.3, 0.7, 1.0, 1.0)
+ CS: (0.3, 0.7, 1.0, 1.5)

**Fig. 6.** The results of CMS with 3 agents

**Table 1.** Performance

| Point num | Loop | Time | Time/Loop |
|---|---|---|---|
| Original Snake | 103 | 0.157 | 0.00152 |
| CMS 10 | 98 | 0.422 | 0.00431 |
| CMS 20 | 78 | 0.359 | 0.00460 |
| CMS 30 | 62 | 0.328 | 0.00529 |

through this experiment, we confirmed that *CMS* using three agents improved the stability of concave detection and also the dependence on a parameter set by reducing a tendency of boundary detection that parameters have. We also performed another experiment employing three agents, that is one sensor-based agent and two model-based agents, and (d) shows its result. This experiment also improved the accuracy of boundary detection.

We adopted thirty feature points in the above-mentioned experiments. Here we show the effect of changing the number of feature points for the detection result. Figure 7 is the result of CMS using the different number of feature point, and Table 1 shows the performance of this experiment. In this regard, we use two agents, one is an original Snake agent with parameter (0.6, 0.4, 1.0) and another is a *Curvature Snake* agent with parameter (0.6, 0.4, 1.0, 1.0). As in Figure 7, the number of feature points affects its result of boundary detection. In Table 1, “Loop” denotes the number of loops and “Time/Loop” denotes the execution time of one loop. The Time/Loop of *CMS* is about three times longer than that of original Snake. It is because of both of curvature calculation on each feature point and calculation of $E_{model}$ and $k_i$.

(a) Using 10 points (b) Using 20 points

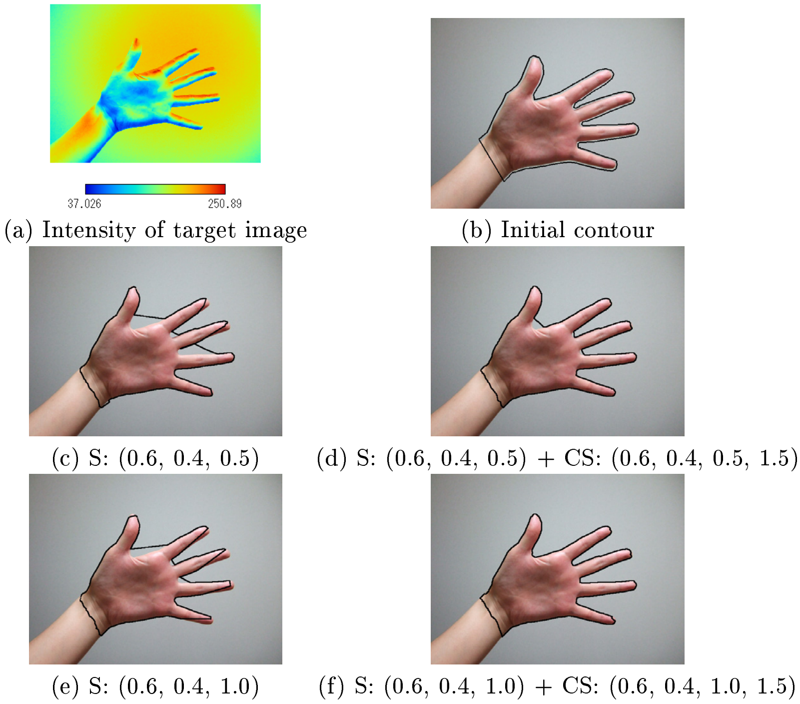
**Fig. 7.** Effects of the Number of Representative Points

Next, Figure 8 is the result of *CMS* using real images. (a) presents the intensity of the image by color gradation, and (b) is the initial contour in black. In this case, the number of control points is 1784 and the number of feature points is 180. (c) is the result of original Snake of parameter (0.6, 0.4, 0.5), and (d) is the result of *CMS* that original Snake of parameter (0.6, 0.4, 0.5) cooperating with *Curvature Snake* with (0.6, 0.4, 0.5, 1.5). Even with *CMS*, it failed to exhibit enough accuracies with these parameter sets. This is caused by the undesired correspondence between the initial and current feature points. The target boundary has some concave regions, and this kind of targets needs some additional technique to correspond between them. Another reason is that the energy potential in the concave region is small. The intensity gradient is small between the target region and the background, and as a result, the force to attract to concave becomes smaller. Because the energy potential is formed by the intensity gradient and the parameters. When $\gamma$ is set larger, (e) is the result of original Snake with (0.6, 0.4, 1.0), and (f) is the result of *CMS* that it cooperates with *Curvature Snake* with (0.6, 0.4, 1.0, 1.5). Through this experiment, *CMS* realized the improvement of stability in the concave region, and we confirmed the improvement of the accuracy.

## 7 Conclusions

Snake's principle can be considered as a boundary detector realized by cooperation in an aggregate of many micro agents, and according to this point, we have proposed *Multi-Snake*, the layered cooperation which integrates the cooperation of the micro agents, who construct a macro agent, to the cooperation of the macro agents. However, the previous *Multi-Snake* used some macro agents of the same kind. In order to improve its estimation quality, and to solve Snake's vulnerability with concave regions, this paper proposed *Curvature Snake*, which adopts a curvature-based shape model based on information out of the initial contour, and also proposed *Curvature Multi-Snake*, layered cooperation of micro agents and macro agents of different kinds. We verified its effectiveness through some experiments.

In the experiments of the single *Curvature Snake*, the drawbacks of Snake to the concave region was improved. However, there is a shape which could not exhibit enough accuracy even with *Curvature Snake*. This was caused by the




(a) Intensity of target image
(b) Initial contour
(c) S: (0.6, 0.4, 0.5)
(d) S: (0.6, 0.4, 0.5) + CS: (0.6, 0.4, 0.5, 1.5)
(e) S: (0.6, 0.4, 1.0)
(f) S: (0.6, 0.4, 1.0) + CS: (0.6, 0.4, 1.0, 1.5)

**Fig. 8.** CMS: $(\alpha, \beta, \gamma)$+$(\alpha, \beta, \gamma, \delta)$ applied to real image

undesired correspondence between the feature points. On the other hand, in the experiments of *CMS* improved the accuracy. In the detection process of *CMS*, we confirmed a tendency that *CMS* chose the agent of the original Snake in the last stages of convergence. This tendency shows that this layered cooperation of macro agents of different kinds is not only improving its accuracy but also this method is more dynamic and flexible. *CMS* can detect the boundary without giving up Snake's advantage which can obtain the smooth boundary.

In general, such kind of the complex shapes used in the experiment of real image is difficult for Snake, and imposes a great deal of labors on a user to set the initial contour and parameters suited for the target shape. *Curvature Snake* and *CMS* also need to set the initial contour with the contrivance for preserving the target shape. That is, the initial contour needs to be set to preserve the target shape such as concavity and convexity. On the other hand, the parameters is set through a certain amount of trial and error. *Curvature Snake* has the force to preserve the shape, so the internal energy $E_{int}$ lessen its grip on Snake. As a result, *Curvature Snake* and *CMS* have an advantage that makes easier to determine parameters for users.

If the initial contour includes concave regions, there is a case of one-to-many correspondence, namely an initial feature point and some current feature points.

We dealt with this issue by selecting the feature point whose interval is shortest between the initial feature point and the current feature point. If *Curvature Snake* and *CMS* failed to detect the boundary because of this kind of correspondence, it will be preventable issue by cooperating with *Curvature Snake* of different number of feature points.

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