Adaptive Color Snake Model for Real-Time Object Tracking

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Abstract: Motion tracking and object segmentation are the most fundamental and critical problems in vision tasks such as motion analysis. An active contour model, snake, was developed as a useful segmenting and tracking tool for rigid or non-rigid objects. Snake is designed on the basis of snake energies. Segmenting and tracking can be executed successfully by energy minimization. In this research, two new paradigms for segmentation and tracking are suggested. First, because the conventional method uses only intensity information, it is difficult to separate an object from its complex background. Therefore, a new energy and design schemes should be proposed for the better segmentation of objects. Second, conventional snake can be applied in situations where the change between images is small. If a fast moving object exists in successive images, conventional snake will not operate well because the moving object may have large differences in its position or shape, between successive images. Snake's nodes may also fall into the local minima in their motion to the new positions of the target object in the succeeding image. For robust tracking, the condensation algorithm was adopted to control the parameters of the proposed snake model called "*adaptive color snake model* (ACSM)". The effectiveness of the ACSM is verified by appropriate simulations and experiments.

Keywords: Active contours, adaptive color snake model, condensation algorithm, object tracking, image segmentation, energy minimization, optical flow, Kalman filter.

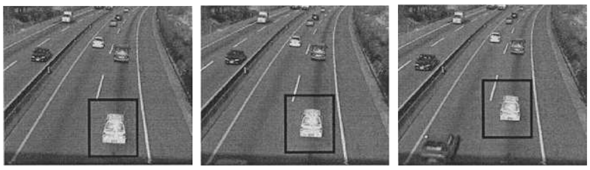
1. Introduction

In recent years, automatic controls have affected the world in various fields. Automation has been carried out in factories, military, services in hospitals, and so on. The controllers of high performance need large amounts of integrated information about systems and the environment for feedback. A vision system is a sensor that is capable of giving this kind of information. Vision sensors are necessary for sensing obstacles or targets in complex systems such as mobile robots, active and intelligent cruise controls. In a vision system, processing such as segmentation and tracking are critical tasks to be accomplished satisfactorily.

A considerable work has been done during the past decade in object tracking and motion analysis of nonrigid objects in the context of snake models. Active contour models have been developed as useful tools for segmenting and tracking rigid and nonrigid objects. Snake, one of the active contour models, was introduced by Kass *et al.* [1] in 1987. They defined snake energies such as internal energy, image energy and external energy. Segmentation and tracking can be done by this energy minimization process. They tried to solve optimization problem for energy minimization by use of the variational approach. They have applied snake to track facial features such as lips in an image sequence. The estimated motion parameters of these features were used to explain facial expressions, etc. Leymarie and Levine [2] have used the snake model to track cells in biological image sequences and proved the convergence of snake's motion. DeCarlo and Metaxas [3] have proposed a deformable face model which includes both shape and motion parameters and have applied it to track human faces. Point distribution based active shape models were also proposed by Kervrann and Heitz [4] to track objects in long image sequences, where a point distribution is used to characterize the structure and variations in the object shape.

Besides the object boundaries, various information in an image or a sequence of images have been used for segmenting objects. Appearance information including grayscale or color have been used in conjunction with deformable shape models [5]. Bascle and Deriche [6] have combined texture correlation of the entire internal region of the object and B-spline contour along the object boundary. Color information has also been used to track nonrigid objects in real-time application [7].

While an active contour model is applied to track an object, stepping to the next image frame in the presence of a large motion difference between them may cause unpredictable effects on the tracking contour. If the variance of the object's location and the configuration between two successive images is large due to the abrupt increase of the object's speed or the low operation speed of the vision system, then the tracking of snake cannot be guaranteed. For the better tracking performance, some advanced algorithms were employed for motion estimation in the snake model. Optical flow algorithm has been commonly applied to estimate the object's motion [3], [8]. But, the computation of the optical flow field for the entire area of interest lead to a considerable computational complexity. It may be effective only for a static camera. As the camera moves, the system generates many variations between successive images. Optical flow-based approach is not suitable for these situations. Another approach is the Kalman filter, a powerful tool for motion analysis [9], which is an frequently used in dynamic estimations. Kalman filtering requires the system to be linear, with its observations be linear functions of the underlying state. The most obvious difficulties of the visual tracking lie in the modeling of the



(a) $(i\text{-}1)$th frame (b) ith frame (c) $(i+1)$th frame

Fig. 1. Example of visual tracking; successful visual tracking involves successive segmentation of boundaries of the target object through a sequential image stream. Target object is framed in the rectangular box.

shape uncertainty and the probability density of the state. Most of the algorithms that use the state-space description are based on Kalman filtering. Kalman filtering has a mechanism that fuse the current noisy measurement information and the estimation based on the history of states. Kalman filtering deals with the uncertainty of the state by carrying the covariance matrices of the states and the measurements, and it works optimally when the noise is Gaussian. This indicates that Kalman filtering algorithm can fail when the uncertainty in the system has multi-modal distribution. This is exactly what happens in the noisy measurement data from an image with several visual clutter, which causes malfunction of the Kalman filter in such situations. The condensation algorithm has been employed in many researches. One of the striking properties of condensation algorithm is its simplicity compared to the Kalman filter. In presence of camera motion, the condensation algorithm shows the robust tracking of object's motion. In following sections, the condensation algorithm will be described in detail.

In this paper, we propose a new snake model, which is capable of dealing with color information. And, we also present a real-time algorithm to track and segment a moving object using the condensation algorithm for better tracking performance. In Section 1, the problem statement is discussed. Section 2 and 3 review the conventional snake and condensation algorithm. The proposed snake model, ACSM and tracking scheme are presented in Section 4 and 5. Experimental results with ACSM on a real video sequence are presented in Section 6. The conclusions are given in Section 7.

2. Problem Statement

Visual tracking involves successive segmentation of the target object's boundaries in a sequence of images. Figure 1 shows three sequential images for visual tracking of a particular object in them. Accurate visual tracking involves the successive segmentation of the object's boundary. Snake's segmentation process is related with energy minimization. Snake energies should be defined in such a way that include the boundary information as minimum energy states. If the minima of the energy surface is found accurately through the energy minimization process, snake can figure out the object's boundary. This is the segmentation process. When the variance of the object's location and the configuration between two successive images is small, snake can also make segmentation of the succeeding image from the contour of the preceding image through the process of energy minimization. This is the tracking process of snake.

When the variance between successive images is small, Kass' snake operates well by the variational solution or dynamic programming method. But in the case of large variance between successive image streams, the convergence of snake motion cannot be guaranteed as the assumptions of variational approach is not effective in such situations. This is a major problem of snake in objects tracking, which may have discrete motions in image streams due to the abrupt increase of object's speed or the low performance of the vision system. Furthermore, when the object moves in a complex background, using only image intensity information is not enough to separate the object from its background. This is another major problem of snake in segmenting objects.

3. Brief Review of Conventional Snake

Kass introduced snake concept in 1987, where he proposed a contour, a deformable curve, and its energies and solutions based on variational approach.

Consider a deformable curve $v(s,t)$ with parameters s (spatial index) and t (time index), defined in given open intervals Ω and T, where it is a function of two variables x and y with the parameterization

$$v(s,t) = (x(s,t), y(s,t)); \quad s \in \Omega, t \in T \tag{1}$$

Kass defined energy terms, that are functions of the contour $v(s,t)$.

Active contour models are the energy-minimizing spline guided by internal constraint forces and influenced by external image forces that pull it toward features such as lines and edges. The conventional energy function in the snake is defined in discrete form as follows:

$$E_{snake} = \sum_{i=1}^{n} \left[E_{int}(i) + E_{image}(i)\right], \tag{2}$$

where n is the number of snake node (called *snaxel* v_i), the internal spline energy $E_{int}(i)$, and the external image energy $E_{image}(i)$, at the ith position of the contour, are described as

$$E_{int}(i) = \alpha_i \left|v_i - v_{i-1}\right|^2 + \beta_i \left|v_{i-1} - 2 \cdot v_i + v_{i+1}\right|^2 \tag{3}$$

$$E_{image}(i) = -\left|\nabla f(v_i)\right|^2 \tag{4}$$

where $f(v_i)$ is the original pixel value at v_i. The symbols α_i and β_i are the weighting factors. The image energy is set to be the negative magnitude of the image gradient, so that the snake is attracted to the regions with low image energy, i.e., strong edges. Thus a snake model is actually a function with a compromise balance between internal and image forces.

4. Condensation Algorithm

The condensation algorithm has attracted much interest in the field of active vision as it offers a framework for dynamic state estimation, where the underlying probability density

function is not required to be Gaussian. The algorithm is based on factored sampling but extended to apply iteratively to successive images in a sequence. As new information becomes available, the posterior distribution of the state variables is updated by recursively propagating these samples.
The state of the modelled object at time t is denoted by $\mathbf{x}_t \in \Re^n$, where as its history is denoted by $\mathbf{X}_t = \{\mathbf{x}_1, \ldots, \mathbf{x}_t\}$. Assuming that the exact state is not known, we describe the knowledge about an object by a probability function $p(\mathbf{x})$. Similarly the measurement of the object at time t is $\mathbf{z}_t \in \Re^n$ with history $\mathbf{Z}_t = \{\mathbf{z}_1, \ldots, \mathbf{z}_t\}$.
A general assumption is made for the probabilistic framework that the object dynamics form a temporal *Markov process* so that

$$p(\mathbf{x}_t|\mathbf{X}_{t-1}) = p(\mathbf{x}_t|\mathbf{x}_{t-1}). \tag{5}$$

The density function $p(\mathbf{x}_t)$ depends only on the immediately preceding distribution $p(\mathbf{x}_{t-1})$, but not on any function prior to $t-1$.
The condensation algorithm describes the sample-based representation of the recursive Bayesian filter and applies factored sampling iteratively to calculate $p(\mathbf{x}_t|\mathbf{Z}_t)$. We always have a sampled distribution $p(\mathbf{x}_t|\mathbf{Z}_{t-1})$, thus, the initial creation of a sample set can be omitted.
An iteration step of the condensation algorithm starts with a sample set $\mathbf{s}$ representing $p(\mathbf{x}_{t-1}|\mathbf{Z}_{t-1})$ from the previous time step. We propagate s to obtain a new sample set $\mathbf{s}'$ according to the system model so that $\mathbf{s}'$ represents $p(\mathbf{x}_t|\mathbf{Z}_{t-1})$. Applying factored sampling, a set $\mathbf{s}''$ is drawn from $\mathbf{s}'$, where each element of the new set is chosen with a probability $p(\mathbf{z}_t|\mathbf{x}_t)$ so that $\mathbf{s}''$ represents the new *a posteriori* density $p(\mathbf{x}_t|\mathbf{Z}_t)$.

5. Adaptive Color Snake Model

Conventional snake has proved to be a very attractive and an efficient method. Although conventional snake provides good results for slow varying object boundaries, it is not suitable for complex situations, where fast motion or abrupt variations of object contours are encountered.
The critical disadvantage of conventional snake is not to utilize the prior knowledge such as color and motion information, which often plays an important role in improving the detection performance in the presence of some disturbing image features (e.g. shadows, shading and neighboring objects). Therefore, our attention is directed towards the use of color and motion information. This consideration provides more accurate results compared to conventional algorithms, in which objects are tracked by exploiting motion information; this is more evident in sequences with complicated content, such as fast motions, complex backgrounds, special camera effects (zooming, pan-tilting), etc.
Approach of ACSM is somewhat different from other approaches that utilize the color information in active contours. Most previous work has been based on the gradient of color intensity, in that a mere extension on gradient of gray image intensity is used. ACSM doesn't depend on gradient of color intensity, but it depends on the stochastic matching degree of color.

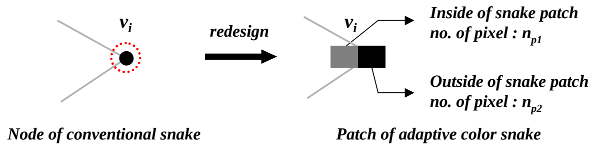


Fig. 2. Design scheme of adaptive color snake model

5.1. Design of Energy for ACSM

We have proposed *color snake model* in previous work. The main idea was the redesign of the snake node, which can deal with color information. But, snaxels in previous research could not adapt color variations. In this paper, we propose a new formulation for ACSM.
The energy functions for ACSM are modified from the conventional snake. As shown in Fig. 2, we have designed a snaxel having two components: outside and inside color patch. These components are compared to the original image where each snaxel lays. This makes the feature/object segmentation process faster and more accurate. The newly proposed energy function is as follows:

$$E_{acs} = \sum_{i=1}^{n} [E_{int}(i) + E_{image}(i) + E_{cs}(i)] \tag{6}$$

$$E_{cs}(i) = -\sum_{k=1}^{n_{p1}+n_{p2}} \{W(p_{i,k}) \cdot D(p_{i,k})\} \tag{7}$$

where

$$W(p_k) = \begin{cases} \begin{bmatrix} w_1 & w_2 \end{bmatrix} & \text{if } p_k \in P_{in} \\ \begin{bmatrix} w_2 & w_1 \end{bmatrix} & \text{if } p_k \in P_{out} \end{cases}$$

$$D(p_k) = \begin{bmatrix} N(z_{p_k}; \bar{z}_{P_i}, \Sigma_1^2) N(\bar{z}_{P_i}; \bar{z}_{P_{i,gen}}, \Sigma_{1,gen}^2) \\ N(z_{p_k}; \bar{z}_{P_o}, \Sigma_2^2) N(\bar{z}_{P_o}; \bar{z}_{P_{o,gen}}, \Sigma_{2,gen}^2) \end{bmatrix}.$$

In $W(\cdot)$, w_1 and w_2 are the user-determined weighting factors for each patch of the snake node. And, a color distribution $N(\cdot)$ can be represented by a Gaussian distribution model as follows:

$$N(z; \bar{z}, \Sigma^2) = \frac{1}{\sqrt{2\pi}\Sigma} \exp\left(-[z-\bar{z}]^T \Sigma^{-2} [z-\bar{z}]/2\right) \tag{8}$$

where
$z = \begin{bmatrix} r & g \end{bmatrix}^T$, $\bar{z} = \frac{1}{n_{p1}+n_{p2}} \sum_{i=1}^{n_{p1}+n_{p2}} \begin{bmatrix} r_i & g_i \end{bmatrix}^T$, $\Sigma = \begin{bmatrix} \sigma_{rr} & \sigma_{rg} \\ \sigma_{gr} & \sigma_{gg} \end{bmatrix}$, and r, g are the normalized color values.
The proposed energy function is composed of three components. First and second terms of (6) are identical to the corresponding terms in the conventional snake model. The first term is the internal energy, its modification will be mentioned in the next section. Third term is the color-fitting term so that ACSM is capable of shrinking until the contour of snake meets the desired color boundary.
In (7), the distribution of general color $N(\bar{z}_i; \bar{z}_{i,gen}, \Sigma_{i,gen}^2)$ was multiplied to the distribution of each color, to prevent the color model from moving too far from the general color.

5.2. Color Adaptation

Most color-based systems are sensitive to change in viewing environment. In general, the color representation of an object viewed with a color camera is influenced by many parameters: ambient light, object movement etc. There are two groups of researches that address environment changes: adaptation and toleration. The adaptive approach provides an alternative to making a color model useful in a large range. Instead of emphasizing the recovery of the spectral properties of light sources and surfaces that combine to produce the reflected lights, the goal of adaptation is to transform the previously developed color model into the new environment. We have adopted a method to adapt the color model. Based on the identification of the desired color histogram, the modified parameters of the model can be computed according to the following process.

In (8), $\bar{z}$ is so noisy that we use the adaptation scheme for determining the color value. Each adapted color value is determined as follows:

$$(\hat{\bar{r}}_k, \hat{\bar{g}}_k, \hat{\Sigma}_k) = \sum_{i=0}^{m-1} (\alpha_{k-i}\bar{r}_{k-i}, \beta_{k-i}\bar{g}_{k-i}, \gamma_{k-i}\Sigma_{k-i}) \qquad (9)$$

where α, β, and γ are scale factors for updating each color.

5.3. Operation Flow of ACSM

The procedure of ACSM is summarized as the following pseudocode.

begin
$t \to 0$ // t: number of iteration
assign manually general color value $\bar{z}_{general}, \Sigma_{general}$
initialize snake node and set initial adaptation color $\bar{z} = \bar{z}_{general}$
while (not termination condition) **do**
  $t \to t+1$
compute energy function using the greedy method
find and move to the point with minimum energy
calculate $\bar{z}$ from the color value within patches
update $\hat{\bar{r}}_k, \hat{\bar{g}}_k, \hat{\Sigma}_k$
end

6. Object Tracking Using Condensation Algorithm

In the previous section, a new design scheme for the segmentation was discussed. In this section a new scheme for tracking is presented. A new snake energy for tracking, and operation modes for the proposed snake are explained as follows:

Segmentation is to separate the boundary of the target object from the images. In the initial state, snake has to be laid roughly around the target object. From this initial position, snake will gradually shrink to the boundary of the target object by minimizing snake energy function. In most of the previous works, this initialization of snake had accomplished manually. However, if the residual motion of the moving object can be detected by processing the condensation algorithm for two successive images, the regional information about the moving object can be stochastically obtained. Thus, automatic initialization can be made possible by using this concept.

7. Experimental Results

7.1. System Setup

We demonstrated the performance of ACSM by applying it to real image sequences. We have implemented the proposed algorithm on a Pentium-IV 2.4 GHz PC with 512MB RAM, and a Logitech QuickCam-Pro USB camera. Three sequential images were captured at the rate of 10 frames/sec. Each image has the resolution of 320×240 pixels and depth of 24-bit color. For simplicity of comparison, 16 snaxels were used for each snake model. For ACSM, initial color distribution of the object was manually assigned. In most object tracking problems, the appearance properties (especially, color information) of target object are known. In the following experiments, however, the color information for outside patch of ACSM are not known, and therefore the energy for outside patch is not required to be calculated. Thus, only inside energy of E_{cs} in (7) is used for experiments. From the second frame, newly adapted color is applied to ACSM. The size of snake patches are 5 pixels each, along the same and opposite directions of the estimated center, which is calculated using the condensation algorithm.

The state vector for Condensation algorithm has the following form:

$$\mathbf{x}_t = [x_t \; \dot{x}_t \; y_t \; \dot{y}_t \; r_t \; \dot{r}_t \; g_t \; \dot{g}_t]^T \qquad (10)$$

where $(x,\ y)$ locates the center of the object, r and g are the normalized color of the object. In the experiments, 100 samples were used at each iteration.

7.2. Experimental Results

Experiments were performed on two cases. First experiment was carried out to test the proposed algorithm for segmenting a fast moving object on a complex background. In the second experiment, the performance was tested in the presence of camera motion. To demonstrate the performance, ACSM was compared with a conventional snake, and a snake with optical flow. Through the experiments, the effectiveness of ACSM was verified.

Case 1: Large motion variance and complex background

The performance of segmentation and tracking in the case of a fast moving object on a complex background is evaluated. Experiments showed that the color information is also essential for object tracking using active contours.

As shown in Fig. 3 and 4, the target object moves across other objects, which are of different colors. Background objects with black color are used, because color difference between background object and the floor is larger than that between target object and the floor, or between target object and background objects. In this experiment, target object moves forward and rotates considerably.

Figure 3 shows the results of conventional snake with motion information using optical flow. From frame 1 to 5, conventional snake works well. But, target object encounters background objects with larger edge intensity from frame 6. Since edge intensity of the background object is larger than

(a)frame 3 (b)frame 7 (c)frame 11 (d)frame 15

Fig. 3. Experimental results for conventional snake with optical flow in case 1.

that of the target object, snaxels tend to be attracted to the boundary of the background object.

Figure 4 presents the results of ACSM. In contrast to results of the conventional snake, ACSM is capable of tracking an object more accurately, since color information of the object is also used. Though the background object with high edge intensity is located near the target object, E_{cs} in (7) attracts snaxels to the object's boundary.

Case 2: With camera motion

Second experiment was carried out in order to show the capability of ACSM in real-time tracking while the camera is in motion. The computation of the optical flow field for the entire area of interest requires considerable computational complexity. Thus, it may be effective only for a static camera. As the camera moves, the system generates considerable variation between two successive images. Therefore, optical flow-based approaches to real-time tracking system need longer calculation time. Therefore, in case 2, conventional snake with optical flow fails to operate in real-time at frame rate of 10 frame/sec as shown Table 2.

We have tested the effectiveness of ACSM on a moving camera system. We have implemented the proposed algorithm on a typical pan-tilt camera system. Tracking and segmentation was performed from frame 1 to 17. Figure 5 presents the results of ACSM. With the color information of the object, ACSM has accurately segmented the object. The condensation algorithm has not been affected by the camera motion. It only considers the probabilistic distribution of desired color information.

7.3. Discussion

In this section, two considerations are described to evaluate the performance of ACSM compared to other approaches. Those are segmentation error and calculation time. In real-time application, those are the most important factors.

7.3.1 Remarks on segmentation error

For comparing with other approaches, two kinds of error measure are accepted as measure for segmentation error. Following measures are the gauge to the accuracy of segmentation. First error measure is given as follows:

$$E_{SCB} = \frac{SCB(n)}{n} \tag{11}$$

where n is the number of snaxels, and $SCB(\cdot)$ refers to the number of snaxels on the correct boundary. This measure converges to 100 % when correct segmentation is done. Second segmentation error is given by

$$E_{card} = \frac{card(T \cap B^c) + card(T^c \cap B)}{card(T)}, \tag{12}$$

where T is the target object mask, B is the background object mask, and $card(\cdot)$ is the the cardinality (i.e., number of pixels) of a set.

Table 1 shows the comparison between conventional snake and ACSM. In order to compare on the same condition, condensation algorithm for tracking method and 50 nodes for snaxels were used to evaluate measures on each frame. And, same initial positions for snaxels were used at each frame. Table 1 says that ACSM is less disturbed than the conventional method, in the presence of background object with high edge intensity and camera motion.

Table 1. Results of Segmentation Error

Case	Segmentation method	E_{SCB} (%)	E_{card} (%)
Case 1	Conventional snake	70.70	69.31
	ACSM	98.58	3.29
Case 2	Conventional snake	63.02	115.85
	ACSM	98.23	2.94

7.3.2 Remarks on calculation time

In real-time systems, calculation time for the proposed algorithm is of great importance. The computational burden in the real-time implementation of the algorithm for object tracking system is the motion estimation. For the better performance of tracking, several advanced algorithms for motion estimation has been employed in the snake model. Optical flow algorithm has been applied to estimate the object's motion. But, the computation of the optical flow field for the entire area of interest requires considerable computational complexity. It may be only effective for a static camera. As the camera moves, the system generates a considerable variation between two successive images. In presence of camera motion, Condensation algorithm shows the robust tracking of object's motion.

Table 2 shows the average calculation time for processing each frame. This table includes the comparison between tracking methods: optical flow and condensation algorithm. As shown in case 1 and 2, in the case of considerably rotating object or camera motion, calculation time for extracting motion vector is too large to operate in real-time. But, ACSM

(a)frame 3 (b)frame 7 (c)frame 11 (d)frame 15

Fig. 4. Experimental results for ACSM in case 1.

(a)frame 5 (b)frame 9 (c)frame 13 (d)frame 17

Fig. 5. Experimental results for ACSM in case 2.

with condensation algorithm is suitable for real-time application.

Table 2. Results of Calculation Time

Case	Segmentation method	Tracking method	Time (ms/frame)
Case 1	ACSM	Optical flow	157
	ACSM	Condensation	89
Case 2	ACSM	Optical flow	373
	ACSM	Condensation	94

8. Conclusion

In this paper, we have introduced a real-time object tracking scheme using a new snake model, called "*adaptive color snake model* (ACSM)" which can be applied to color image segmentation and object tracking. Through experiments, the effectiveness of the proposed algorithm was verified.

Experimental results show the potential of the proposed ACSM and tracking scheme. Despite the fast motion, complex background, special camera effects, ACSM can also operate in real time. Therefore, proposed tracking scheme is more suitable than intensity-based or optical flow-based approaches.

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