Active Rays: A New Approach to Contour Tracking

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In this paper we describe a new approach to contour extraction and tracking, which is based on the principles of active contour models, yet it overcomes its shortcomings. We formally introduce *active rays*, describe the contour extraction as an energy minimization problem and discuss what active contours and active rays have in common.

The main difference is that for active rays a unique ordering of the contour elements in the 2D image plane is given, which cannot be found for active contours. This is advantageous for predicting the contour elements' position and prevents crossings in the contour. Furthermore, another advantage of this approach is that instead of an energy minimization in the 2D image plane the minimization is reduced to a 1D search problem. The approach also shows any–time behavior which is important with respect to real–time applications. Finally, the method allows for the management of multiple hypotheses of the object's boundary.

First results on real image sequences show the suitability of this approach for real–time object tracking. The contour tracking can be done within the image frame rate (25 fps) on standard Unix workstations (HP 735).

Keywords: active contour models, tracking, real-time.

1. Introduction

The field of real–time computer vision has become more and more important in the past 10 years. Due to the increasing hardware performance and to new strategies for the processing of images and of image sequences (active vision, [2]), applications, which work in a closed loop between sensing and action, have been developed recently [6, 11]. Especially, for real–time object tracking many algorithms can be found in the literature [3, 5, 7]. One class of algorithms is the so called active contour model (snake) [9], which allows for data driven contour segmentation, extraction, and tracking. They are well suited for real–time applications due to the inherent local processing of an image nearby the snake elements. In front of a homogeneous background moving objects can be robustly tracked in real–time [4, 13]. Introducing a prediction step, a certain quantity of inhomogeneous background can also be allowed. Finally, this approach is insensitive with respect to different camera devices and changes in the camera parameters (focus, zoom, aperture); it is also robust to changing lighting conditions, even during the tracking.

But this contour tracking method still has some limitations. Strong background edges near the object's contour are also good minima for the energy minimization of the active contour. Thus, in natural scenes special task specific constraints [12, 15] are necessary to increase the computation time and reduce the real–time performance. Without such task specific constraints tracking may fail. Another problem is the missing order of snake elements in the 2D image plane. During the energy minimization crossings in the contour might occur [16] resulting in an incorrect contour extraction (see Figure 1, left). There are algorithms [16], which can handle this case, but they also increase the computation time of the algorithm. Another problem arises from the missing order in the 2D image plane. Even if no crossing of the contour occurs, one cannot find any logical correspondence between active contour elements and points at the contour of the moving object. This means, one cannot predict actually to which point a single snake element moves. Only the movement and — to a certain extent — the distortion of the whole active contour can be predicted (see Fig-

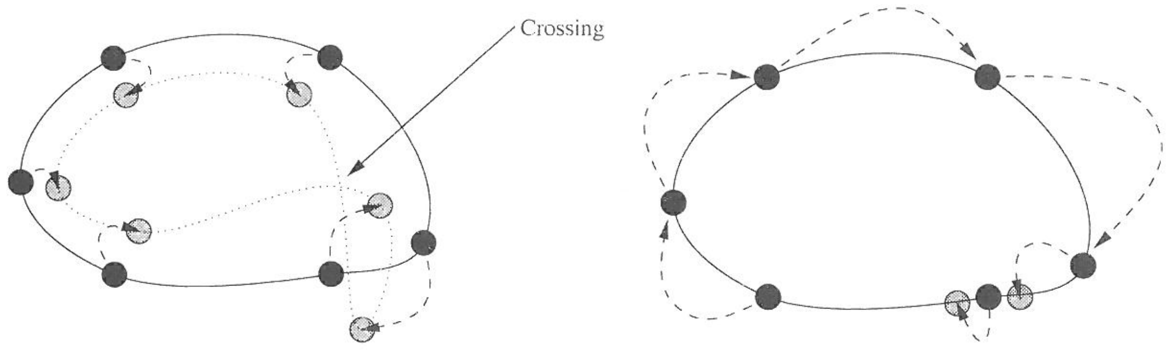


Fig. 1. Two main problems of active contours during tracking, which result from the missing ordering in the 2D image plane: Crossings in the 2D contour may occur (left). The snake elements are not fixed at logical features on the object's contour, but they may move around the contour as they like (right).

ure 1, right: the shape of the contour remains the same, although all the snake elements have moved around the contour). Finally, no work is known that adds some any–time behavior to active contours. Of course, an iterative minimization can be seen as an any–time algorithm. Reducing the iteration steps in one image results in a less accurate extraction of the object's contour. But within the next images snake elements might remove from the sphere of influence of the object's contour and thus lose the moving object.

This problem is explained in Figure 2. A 1D contour is shown at three different times (t_1, t_2, t_3), moving along the x–axis. The snake element at time t_1 (black circle) is in the sphere of influence of the 1D contour. By moving downhill the contour, after some iterations it reaches the minimum. At time t_2 the contour element is again in the sphere of influence. This allows moving downhill to the minimum. Now the iteration number is reduced, which means that the energy minimization stops before the real minimum is reached. Then, at time t_3 the snake element (gray circle) is not in the sphere of influence of the 1D contour and cannot reach the true minimum. Thus, the contour is lost.

In this paper we propose a new approach to contour extraction and tracking, which we call *active rays*. These active rays contain principles of active contour models (i.e., energy minimization, local processing of the image, contour representation of the moving object) and therefore overcome the mentioned shortcomings. To be more precise, active rays

- show any–time behavior,
- reduce the 2D energy minimization of snakes to a 1D search problem,
- allow for using multiple hypotheses for the object's boundary, and
- have a fixed 2D order of the contour elements.

In Sect. 2 we formally introduce active rays and present an energy description of the common parts of active contour models and active rays. In Sect. 3 we apply active rays to contour tracking and show the possible any–time behavior. First experiments and results related to real–time object tracking can be found in Sect. 4. The paper ends with a summary and discussion (Sect. 5) and an outlook to future work (Sect. 6).

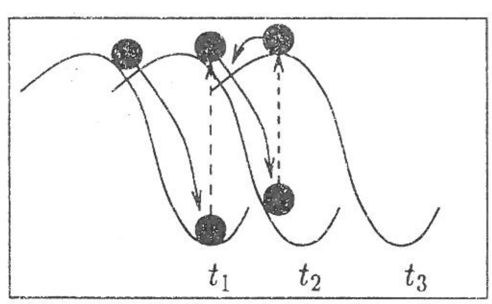


Fig. 2. Problem, when reducing the number of iteration steps during the energy minimization while tracking a 1D signal (time t_1, t_2, t_3).

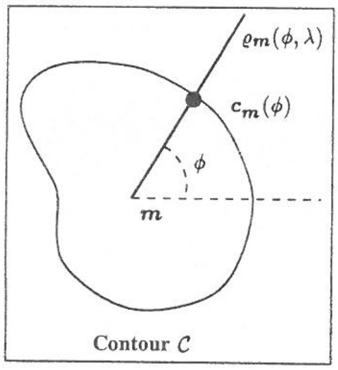


Fig. 3. Principle of one active ray.

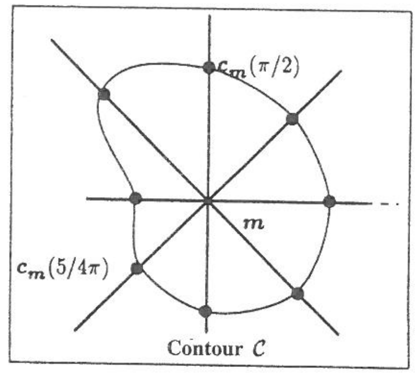


Fig. 4. Representation of a contour by active rays.

2. Active Rays

This section is divided into three parts. First, a formal description of active rays is given. In the second part we formulate the contour extraction as an energy minimization problem and we compare active contour models to active rays. Finally, we motivate the use of multiple hypotheses and the any–time behavior of our proposed method.

2.1. Formal Description

An active ray $\varrho\boldsymbol{m}(\phi, \lambda)$ is defined on the image plane (x, y) as a 1D function depending on those gray values $f(x, y)$ of the image, which are on a straight line from the image point $\boldsymbol{m} = (x_m, y_m)^T$ in direction ϕ

$$\varrho\boldsymbol{m}(\phi,\ \lambda) = f(x_m + \lambda\ cos(\phi), y_m + \lambda \sin(\phi)),\quad 0 \leq \lambda \leq n_\phi, \tag{1}$$

where n_ϕ is given by the image size. The principle is clarified in Figure 3. The angle ϕ is measured counter clockwise.

Now, a contour point in direction ϕ regarding a given reference point $\boldsymbol{m}$ can be described by the parameter $\lambda(\phi) \geq 0$

$$\begin{aligned}\lambda(\phi) &= \text{argmin}_\lambda \left(-|\nabla f(x_m + \lambda \cos(\phi),\right.\\ &\qquad \left. y_m + \lambda \sin(\phi))|^2\right)\\ &= \text{argmin}_\lambda \left(-\left|\tfrac{\partial}{\partial\lambda}\varrho\boldsymbol{m}(\phi, \lambda)\right|^2\right),\\ &\qquad 0 \leq \phi < 2\pi, \end{aligned}\tag{2}$$

i.e., we are looking for points on the active ray with a maximum edge strength. The contour point $\boldsymbol{v}\boldsymbol{m}(\phi)$ (see Figure 3) is then

$$\boldsymbol{v}\boldsymbol{m}(\phi) = (x_m + \lambda(\phi) \cos(\phi), y_m + \lambda(\phi) \sin(\phi)),\quad 0 \leq \phi < 2\pi \tag{3}$$

A similar representation is used by the generalized Hough transform. In a discrete case the whole contour can be computed by defining a sampling step size $\triangle\phi$ for ϕ. This allows different accuracy of the contour representation. An example of a contour representation is shown in Figure 4. The sampling step size $\triangle\phi$ is $\pi/4$.

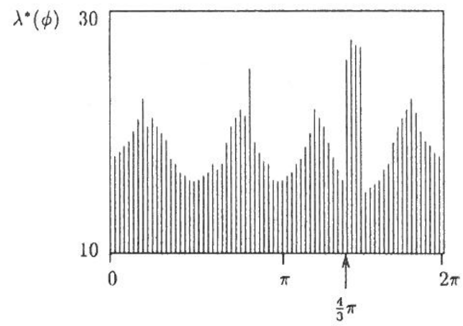
Now, we have to discuss the choice of the reference point $\boldsymbol{m}$. In principle, every point within the object's contour is possible. But to have a unique point, which can be precalculated by a prediction step, the center of gravity of the contour extracted by the active ray is used in the following, i.e., the equation

$$\boldsymbol{m} = 1/2\pi \int_0^{2\pi} \boldsymbol{v}\boldsymbol{m}(\phi)\, d\phi \tag{4}$$

should hold for the reference point $\boldsymbol{m}$. For convex contours $\boldsymbol{m}$ will also be the center of gravity of the object's contour. What happens, if the chosen reference point is not the center of gravity? Then, we can calculate a new reference point using the formula (4). After that, the new contour representation has to be calculated.

2.2. Definition of an Energy Term

Equation (2) leads to single contour points without taking into account the global shape of the underlying contour. Thus, errors might occur for real images due to noise in the image or background edges near the object. Without coupling



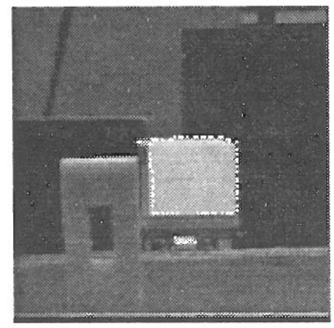


Fig. 5. Left: The function λ for the contour shown in the right image: one point of the x–axis is equal to five degrees.

neighboring contour points the function λ normally will not correctly represent the contour. This can be seen in Figure 5, where the function λ for the contour in Figure 5 (right) is shown. For the angles $\phi \in [4/3\pi, 3/2\pi[$ a strong edge is extracted, which does not belong to the contour corresponding to $\lambda(\phi)$, $\phi \notin [4/3\pi, 3/2\pi[$. In Figure 5 this results in four values of λ (x–axis: $\frac{4}{3}\pi - \frac{3}{2}\pi$), which are outliers in this function plot.

A common technique to solve this problem is defining an internal energy to connect contour elements of the active ray (see equation 3). For snakes a common definition of the internal energy $E_i(\boldsymbol{v}(s))$ of an active contour element $\boldsymbol{v}(s)$ is (cf. [9])

$$E_i(\boldsymbol{v}(s))=\frac{\alpha(s)|\boldsymbol{v}_s(s)|^2+\beta(s)|\boldsymbol{v}_{ss}(s)|^2}{2}, \quad (5)$$

with $\boldsymbol{v}_s(s)$ and $\boldsymbol{v}_{ss}(s)$ being the first and second derivatives of $\boldsymbol{v}(s)$. This energy definition weighted by $\alpha(s)$ and $\beta(s)$ describes the membrane and thin plate behavior of a snake [9]. For an active ray the same behavior can be produced by defining

$$\begin{aligned} E_i(\boldsymbol{v}(s)) &= E_i(\boldsymbol{v}_{\boldsymbol{m}}(\phi)) \\ &= \frac{\alpha(\phi)|\frac{d}{d\phi}\boldsymbol{v}_{\boldsymbol{m}}(\phi)|^2+\beta(\phi)|\frac{d^2}{d\phi^2}\boldsymbol{v}_{\boldsymbol{m}}(\phi)|^2}{2}. \quad (6)\end{aligned}$$

In the case of an active ray, a reference point is given. Thus, a better definition of the internal energy $E_i(\boldsymbol{v}_{\boldsymbol{m}}(\phi))$ is

$$\begin{aligned} E_i(\boldsymbol{v}_{\boldsymbol{m}}(\phi)) &:= E_i(\phi) \\ &= \frac{\alpha(\phi)|\frac{d}{d\phi}\lambda(\phi)|^2+\beta(\phi)|\frac{d^2}{d\phi^2}\lambda(\phi)|^2}{2}. \quad (7)\end{aligned}$$

The function $\lambda(\phi)$ is given by equation (2). Now we need an external energy. Let us take the usual image gradient, i.e.,

$$\begin{aligned} E_e(\boldsymbol{v}_{\boldsymbol{m}}(\phi)) &= -|\nabla f(\boldsymbol{v}_{\boldsymbol{m}}(\phi))|^2 \\ &= -\left|\tfrac{d}{d\lambda}\varrho_{\boldsymbol{m}}(\phi,\lambda)\right|^2 \quad (8)\end{aligned}$$

Equations (7) and (8) both need computations only for a 1D signal, compared to the energy definitions of an active contour, which needs a 2D minimization. This is advantageous for real–time applications.

2.3. Energy Minimization

After a formal description of an active ray and its internal and external energy, we can go on formulating the contour extraction as an energy minimization problem. For this purpose, the same formalisms as for active contour models can be applied (for example, the Greedy algorithm [14], dynamic programming [1], etc.).

Total energy of an active ray, which is uniquely given by the function $\lambda(\phi)$ and a reference point $\boldsymbol{m}$, can be defined as

$$\begin{aligned} E &= \int_0^{2\pi} \left[E_i(\lambda(\phi)) + E_e(\lambda(\phi))\right] d\phi \quad (9) \\ &= \int_0^{2\pi} \left[\frac{\alpha(\phi)|\frac{d}{d\phi}\lambda(\phi)|^2+\beta(\phi)|\frac{d^2}{d\phi^2}\lambda(\phi)|^2}{2}\right. \\ &\qquad \left. -\left|\tfrac{d}{d\lambda}\varrho_{\boldsymbol{m}}(\phi,\lambda)\right|^2\right] d\phi \quad (10)\end{aligned}$$

Now, we are looking for a function $\lambda(\phi)$, which minimizes this energy E, i.e., we have to solve the Euler–Lagrange differential equation

$$\begin{aligned} &\alpha(\phi)\tfrac{d^2}{d\phi^2}\lambda(\phi) - \beta(\phi)\tfrac{d^4}{d\phi^4}\lambda(\phi) \\ &\quad + \tfrac{d}{d\lambda}\left|\tfrac{d}{d\lambda}\varrho_{\boldsymbol{m}}(\phi,\lambda)\right|^2 = 0. \quad (11)\end{aligned}$$

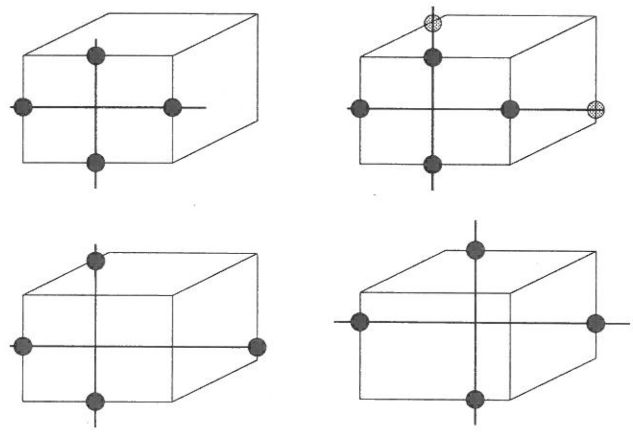


Fig. 6. Principle of the hypotheses management for contour points.

This can be done in the discrete case by using an iterative algorithm [9].

2.4. Multiple Hypotheses and Any–Time Behavior

In the introduction we noted that the approach of active rays allows for multiple hypotheses. We have to look for the i best solutions of equation (2), which means, that for each ray in the direction ϕ we get a set $\Lambda(\phi)$

$$\begin{aligned}\Lambda(\phi) &= \{\lambda_k(\phi) | \lambda_k(\phi) \\ &= \operatorname{argmin}_{\lambda, \lambda \neq \lambda_l, l<k} \left(- \left| \frac{\partial}{\partial \lambda} \varrho \boldsymbol{m}(\phi, \lambda) \right|^2 \right), \\ &\quad 0 \leq k < i\} \end{aligned} \tag{12}$$

of possible solutions for the contour instead of one single contour element. Then, multiple boundary elements lying on one ray can be handled too, which is necessary if concave contours shall be tracked.

The principle of any–time behavior of active rays can be summarized as follows. If more than one object should be tracked, or if the objects are moving very fast, then increase $\triangle\phi$ of the angle ϕ. If you have more time or you need a more accurate contour representation, reduce $\triangle\phi$ by filling some lost angles into the active ray. For example, start with the angles $\pi/2$, π, $3/2\pi$ and 2π. Then, if there is time, add the angles $i/4\pi, i \in \{1, 3, 5, 7\}$, then the angles $i/8\pi, i \in \{1, 3, 5, 7, 9, 11, 13, 15\}$, etc.

3. Active Rays for Object Tracking

In the previous section we gave an introduction and a formal definition of active rays, together with an energy minimization scheme. For object tracking several aspects have to be examined: Initialization of an active ray, strategy for choosing a suitable number and directions of the active rays, as well as strategy for managing multiple hypotheses. Finally, to reduce the computation time, certain search intervals have to be selected. Some of these points will be discussed here, some others will be the subject of our future work.

To initialize an active ray, a point within the contour of the moving object must be found. This can be done by using a static camera and computing the difference image. The gravity center of the difference is well suited as the first reference point $\boldsymbol{m}$. Certain information about the size of the object moving in different directions can be computed as well.

Shooting an active ray from this reference point may result in finding strong edges within this object, which are not contour edges (step 1 in Figure 6). This is especially a problem, if no information about the size of the object is available. Then, one possible approach is to let the active ray grow for each image, until a new contour point is found which satisfies (2) (step 2 in Figure 6). If this new hypothesis is verified within the next images, take it as the new contour element, update the reference point $\boldsymbol{m}$, and search for the next hypothesis (step 3 and 4 in Figure 6). Due to the lack of space the verifica-

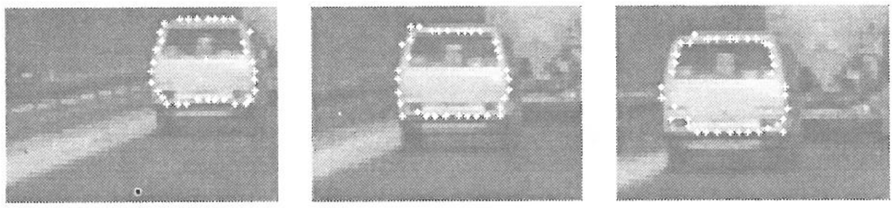


Fig. 7. Results for tracking a car on a highway with active rays (images 4, 44, 84 of a sequence of 123 images taken at video rate): the sampling step size $\triangle\phi$ is $\pi/18$.

tion step cannot be described any further in this paper.

For each active ray $\varrho\boldsymbol{m}(\phi,\lambda)$ and for the contour element $\boldsymbol{v_m}(\phi)$ one can define a search interval $I(\phi)$ for λ for the next image. This search interval can be computed by a prediction step, or it may depend on $\lambda(\phi)$ of the previous image or the neighboring elements. So, only a small part of $\varrho\boldsymbol{m}(\phi,\lambda)$ must be examined to find the maximum, and equation (2) gets

$$\lambda(\phi) = \mathrm{argmin}_{\lambda\in I(\phi)} \left(-\left|\frac{\partial}{\partial\lambda}\varrho\boldsymbol{m}(\phi,\lambda)\right|^2\right), \quad 0\le\phi<2\pi. \tag{13}$$

In the introduction the missing ordering of snake elements in the 2D image plane was mentioned as a problem for predicting the motion of single contour elements. Only the motion of a complete contour can be predicted. For active rays, implicit ordering in the 2D image plane has been defined, given by the angle of the rays and the reference point. This can be used, if a 2D contour has been predicted, by estimating the 3D parameters of the moving object. Then, the reference point $\boldsymbol{m}$ of the predicted contour as well as the rays in arbitrary directions can be calculated in advance and verified for the real image data. Results related to the real data can then be used to update the predicted object parameters.

4. Experiments and Results

Preliminary experiments for extracting and tracking a contour with active rays have been conducted. Neither multiple hypotheses nor a prediction step have been applied yet. This will be the subject of our work in the near future. All experiments are done off–line.

$\triangle\phi$	time/image (msec)
$\pi/180$	38
$\pi/36$	19
$\pi/18$	16
$\pi/9$	10

Fig. 9. Computation time for one image for different sampling step sizes $\triangle\phi$.

Figure 7 show the results for tracking a moving car on a highway. The sampling step size $\triangle\phi$ has was $\pi/18$. Computation time for extracting the contour for all 123 images of this sequence was 1.98 sec, i.e., 16 msec/image on a HP 735/99 MHz. The reference point $\boldsymbol{m}$ was chosen manually in the first image. For all other images the computed center of gravity for the active ray in image t was taken as the initial reference point for image $t+1$. In Figure 8 results of the same sequence for $\triangle\phi = \pi/9$ can be seen. Results of the computation time for different sampling rates can be found in Figure 9.

Fig. 8. Results for tracking a car on a highway with active rays (images 4, 44, 84 of a sequence of 123 images taken at video rate): the sampling step size $\triangle\phi$ is $\pi/9$.

5. Conclusion

In our paper we have presented a new approach to contour tracking, called active rays. The basic ideas come from active contours, which have been proven to be a promising approach to data driven real–time contour tracking.

Active rays have the following advantages over active contour models:

- For active rays ordering in the image plane is given by a reference point $\boldsymbol{m}$ and an angle ϕ. Thus no crossings occur and predicting the position of contour elements is possible.
- All optimization problems are reduced to 1D search problems.
- Active rays provide a mechanism, to select the required accuracy of the contour approximation. This leads to an any–time behavior, which is an important aspect of real–time applications.
- Active rays provide a mechanism to manage multiple hypotheses, which is useful to detect the contours which appear due to changing views of the object.

We have presented a formal description of active rays and an energy formulation for the contour extraction. In addition, we have shown the common parts of active contours and active rays. The experiments have proven that this new approach is well suited for an accurate contour extraction and real–time tracking.

6. Future Research

In Sect. 2 and Sect. 3 we already mentioned the mechanism of multiple hypotheses, the possibility of an any–time realization and the advantages of predicting the position of contour elements. These topics are examined in our actual work. We will compare the active ray approach with active contour models on a larger test set, also in a closed–loop real–time application [6].

Finally, another important aspect of any problem in image processing or in general pattern recognition is the ability of self–adaption or learning. For example, learning 3D models of objects from greylevel images [8], or deformation of contours in the image plane [10]. Today all state of the art speech recognition systems use a training set to estimate the parameters of the system. For contour tracking one has to learn the possible deformation of the contour occuring due to rotation and translation. Then, having inspected movement of the object during a training step, one can predict deformation of the contour even for occlusions. A lot of work on this aspect is still required. Our remarks should only give a coarse idea of how active rays can be trained.

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