Active contour와 Optical flow를 이용한 카메라가 움직이는 환경에서의 이동 물체의 검출과 추적

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A Method of Segmentation and Tracking of a Moving Object in Moving Camera Circumstances using Active Contour Models and Optical Flow

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Abstract

In this paper, we propose a new approach for tracking a moving object in moving image sequences using active contour models and optical flow. In our approach object segmentation is achieved by active contours, and object tracking is done by motion estimation based on optical flow. To get more dynamic characteristics, Lagrangian dynamics combined to the active contour models. For the optical flow computation, a method, which is based on Spatiotemporal Energy Models, is employed to perform robust tracking under poor environments. A prototype real tracking system has been developed and applied to a contents-based video retrieval systems.

1. Introduction

The segmentation and tracking of a moving object is one of the most important techniques in computer vision. It is needed for many real-time systems as well as to improve the compression ratio in MPEG-4. A subclass of these issues, and probably the most difficult one, is the motion analysis and tracking of non-rigid objects such as the human body and muscle actions. Tracking techniques for such objects include boundary detection via active contour methods and optical flow based motion analysis. Using these methods, we propose a new algorithm for boundary tracking and motion analysis of a moving object. Boundary tracking based on deformable contour model, known as snakes, was originally introduced by Kass and Terzopoulos et. al. (eg. [1], [2]). Snake is a deformable contour that moves under the influence of the image forces, with certain internal deformation constraints. Gradient based image potential, for example, results in edge-based image forces, leading the contour towards low potential boundaries, thus achieving boundary tracking.

Typically, object tracking using the active contour models suffers from two major problems. The first relates to the background conditions which, while tracking an object, forces the contour towards other image boundaries. The second problem is due to that the contour evolves under the influence of a single image. While stepping to the next image, if the contour has been not converged or the boundary disappears temporary due to illumination conditions or occlusions, it may effect unpredictable effects on the tracking performance.

These problems could be overcome if information about the motion of the object to track is known. Motion estimation from a sequence of images is done based on optical flow. Several ways of computing the optical flow have been proposed. Especially, a method, which is based on spatio-temporal energy models, is applied to the moving object that have not clear features to apply a differential method based motion estimation. Object tracking using active contours and optical flow, we propose a new tracking scheme in which the tracking process is achieved by active contours guided by optical flow. This leads to a new method for tracking a visually indistinct objects equipped with boundary tracking and optical flow estimation,

2. Preliminaries

In this section we present the active contour model originally proposed by Kass and Terzopoulos et. al. [1], [2], and the optical flow estimation using spatiotemporal energy model [4].

2.1 The active contour model

The active contour model proposed by Kass is

$$E(v) = E_s(v) + P(v) \tag{1}$$

where

$$E_s = \int_0^1 w_1(s)|v_s|^2 + w_2(s)|v_s|^2 ds \tag{2}$$

and

$$P(v) = \int_0^1 \pm c|\nabla|G_\sigma * I(v(s))||ds \tag{3}$$

$E_s(v)$ is deformation energy of the contour, where v represents the contour as a mapping from the unit parametric domains $s \in [0,1]$ into the image plane R^2 and R^3. The components of the mapping $v(s)$ = $(x(s),\ y(s))$ are the contour's coordinates functions. w_1 and w_2 represents "tension" and "rigidity" of the contour respectively. $P(\mathrm{v})$ represents intensity edges of the image. We combine this model with Lagrangian dynamics. We can represent a dynamic snake by introducing a time-varying mapping $v(s,t)$ and a kinetic energy. The Lagrangian formulation of active contour is

$$L(v) = \frac{1}{2}\int_0^1 \mu|v_t|^2 ds - \frac{1}{2}E(v) \tag{4}$$

where μ is mass density.

The dynamic equation of the model is obtained by calculus of variation and some initial conditions. If the Rayleigh dissipation function is incorporated to dissipate kinetic energy, the Lagrangian equation is

$$\begin{aligned} \frac{d}{dt}\left(\frac{\delta L}{\delta v_t}\right) + \frac{\delta L}{\delta v_t} - \frac{\delta L}{\delta v} + \frac{\delta}{\delta s}\left(\frac{\delta L}{\delta v_s}\right) \\ - \frac{\delta}{\delta s^2}\left(\frac{\delta L}{\delta v_{ss}}\right) = 0 \end{aligned} \tag{5}$$

Assuming constant mass density and constant dissipation, the resulting Euler-Lagrange equation of the model is

$$\begin{aligned} \mu v_{tt} + \gamma v_t - \frac{\delta}{\delta s}(w_1 v_s) + \frac{\delta^2}{\delta s^2}(w_2 v_{ss}) = \\ - \nabla P(v(s,t)) \end{aligned} \tag{6}$$

The differential equation could be solved by the Finite Element Methods. To adapt the lagrangian dynamic equation for FEM, the discretized version of lagrangian dynamic equation (6) is employed. The formulation is

$$M\ddot{u} + C\acute{u} + Ku = f \tag{7}$$

where,

$$K = \begin{bmatrix} a_0 & b_0 & c_0 & & & & c_{N-2} & b_{N-1} \\ b_0 & a_1 & b_1 & c_1 & & & & c_{N-1} \\ c_0 & b_1 & a_2 & b_2 & c_2 & & & \\ & c_1 & b_2 & a_3 & b_3 & c_3 & & \\ & & \ddots & \ddots & \ddots & \ddots & \ddots & \\ & & & c_{N-5} & b_{N-4} & a_{N-3} & b_{N-3} & c_{N-3} \\ c_{N-2} & & & & c_{N-4} & b_{N-3} & a_{N-2} & b_{N-2} \\ b_{N-1} & c_{N-1} & & & & c_{N-3} & b_{N-2} & a_{N-1} \end{bmatrix}$$

$$u_i = v(ih) \text{ for } \mathrm{i} = 0, \ldots, \mathrm{N}-1, \text{ where } \mathrm{h} = 1/(\mathrm{N}-1)$$

$$a_i = (w_{1i-1} + w_{1i})/h^2 + (w_{2i-1} + 4w_{2i} + w_{2i+1})/h^4$$

$$b_i = -w_{1i}/h^2 - 2(w_{2i} + w_{2i+1})/h^4, \quad c_i = w_{2i+1}/h^4$$

Here, M is the mass matrix, and C is a damping matrix. If we replace the time derivatives of u with the backward finite differences. The update formula is then obtained as

$$Au^{(t+\Delta t)} = b^{(t)} \tag{12}$$

where

$$A = M/(\Delta t)^2 + C/2\Delta t + K$$

$$b = (2M/(\Delta t)^2)u^{(t)} - (M/(\Delta t)^2 - C/2\Delta t)u^{(t-1)} + f^{(t)}$$

The formula (13) could be solved efficiently by factorizing A into lower and upper triangular matrices, then solving the two resulting sparse triangular systems.

2.2 The spatiotemporal energy model

The spatiotemporal energy model is based on human perception of motion. In this method, optical flow could be estimated by using several gabor filters with different gabor filters. The response of each right and left oriented filter for an edge moving sinusoidally is illustrated in Fig.1 and Fig.2.

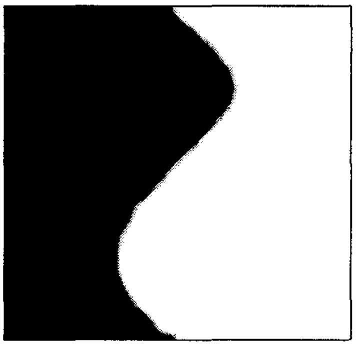

Fig. 1, An (x,t) plot of an edge moving sinusoidally

Fig. 2. a, The response of a right oriented gabor filter for Fig. 1

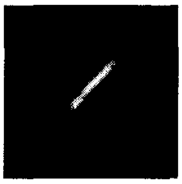

Fig. 2. b, The response of a left oriented gabor filter for Fig. 1

As shown above, the spatiotemporally oriented filters are quite useful in analyzing motion, but they pose some difficulties as they stand. They are phase sensitive, which is to say that their response to the moving pattern happens to line up with their receptive field at each moment. Thus, as an example, the response for a moving sine-wave grating will oscillate over time. This problem could be solved by building quadratic pairs of filter. Each oriented gabor filter and its quadratic pair is shown in Fig.3. By squaring and summing the each reponse of the quadratic pair, the local motion energy could be measured. Another problem is that the contrast of the image affects to the motion energy. This problem could be compensated by using one more channel. Fig.4 suggests a scheme in which velocity is derived by comparing the outputs of several channels within the same spatial-frequency band. The three Gaussian-like curves in Fig.4 represent the sensitivities of a leftward, a static, and a rightward-sensitive channel. If the contrast of the stimulus is changed, the absolute value of the responses will change, but the ratios between them will remain fixed, as long as each channel's response grows in proportion to the contrast of the input.

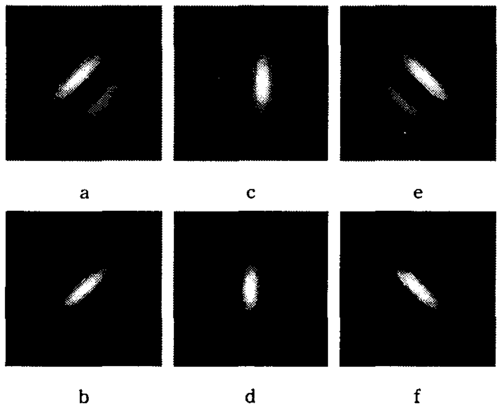

Fig. 3. a-b, two left sensitive quadratic pairs of oriented gabor filter, c-d, two static sensitive quadratic pairs of oriented gabor filter. e-f, two right sensitive quadratic pairs of oriented gabor filter.

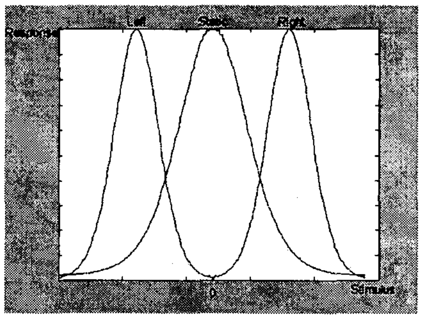

Fig. 4. The response curves of thee motion units plotted as a function of velocity.

3. Active contours guided by Optical flow

In this section, we incorporate the active contour model with motion estimation. To guide active contours to proper direction, optical flows are estimated at each moment. Optical flow is computed for horizontal and vertical direction independently at each contour point. Optical flows estimated on the boundary represents the velocity of the contours, thus we can predict the contour's position in the next frame. In case there is wrong estimation of motion, to compensate the error, computed velocities are interpolated. But, in camera moving circumstances, the estimated velocity on the contour will not be reliable information. Therefore, the motion estimation is performed on the interior and exterior region of the object. These results represents the object and camera motion. The difference between the velocity of the object and camera also represents the relative velocity in the image. The velocity at the contours and the difference of the velocity on the interior and exterior region are both contain the information of the object motion. We use the weighted sum of the two results as a contour motion.

4. Experimental Results

Tracking results represented in Fig. 5 shows a set of frames in image sequence. A circle moves right and down direction over time with zooming in, and the background also moves. As we showed, the moving circle could be tracked at each moment (at each 50 frame).

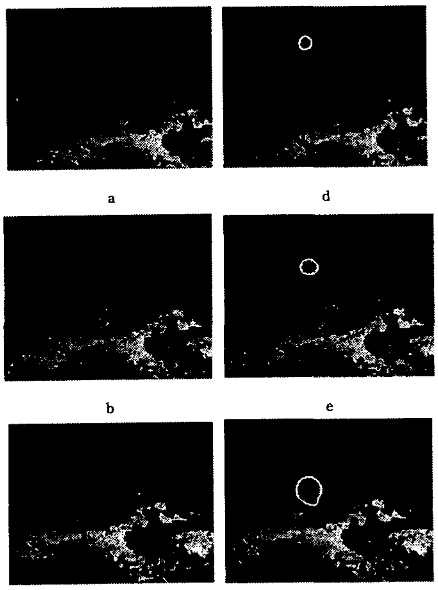

Fig. 5. A circle moves in moving image sequences, a-c; the original video sequences. d-f; Tracking results of active contours combined with optical flow.

For tracking the growing circle, the idea of Balloon [3] is employed. In edge detection, we use the Canny edge detector as implemented recursively by Deriche [6]. We simulated proposed algorithm under various conditions to improve the tracking performance. In computation of optical flow, to reduce the computational time, we introduced the hierarchical discrete correlation (HDC) [5] into motion estimating process.

5. Conclusion

We have described a new approach of tracking method which results from combining active contour models and optical flow. To get more dynamic characteristic, Lagrangian dynamics is combined to active contour models. Spatiotemporal energy model is employed to estimate the optical flow. The proposed algorithm is applicable to many tracking issues containing camera motion. Although, the computational cost of optical flow is still intensive, this could be overcome using independent parallel processing units.

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