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An Optical Flow Method for Motion Estimation and Segmentation

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Abstract

Motion estimation and segmentation has been one of the most important prerequisite tasks for many computer vision applications such as surveillance, tracking, human-machine interface. Many previous approaches have problem of robustness under unexpected situations such as large illumination changes. In this paper, we propose a motion segmentation method based on robust illumination invariant optical flow estimation.

Key words: Motion estimation, Optical flow, Segmentation, Illumination invariant.

1. Introduction

Motion-based image segmentation algorithms seek to partition an image into regions on the basis of the properties of the motions observed in pixels. That a motion property can serve as a good basis for grouping pixels together is intuitively obvious and has been recognized by the research community for a long time [1]. It has also been recognized that adding motion as a criterion for segmentation can alleviate some of the shortcomings of the more traditional algorithms that try to segment an image on the basis of static attributes such as intensity, edge, color, and texture. Unfortunately, estimating motion parameters from a sequence of images is still not easy, though much research has been conducted in this area [2]. This makes motion-based segmentation of images quite difficult.

The simplest approach to segmenting moving objects in an image sequence is to find differences between consecutive images in a video sequence [3]. Though such differencing provides information about the locations of moving pixels and the gross motions associated with a region, it does not estimate motions precisely enough to use other motion estimation techniques such as the optical flow method. For more precise motion-based segmentation, in most cases, one must resort to multiple motion estimation. Obviously, if a multiple motion estimator is performing well, it would be easy to group the pixels together on the basis of the motions corresponding to the different objects. Mitiche [4] has classified the more advanced techniques (that is, techniques more advanced than the differencing method and possibly using multiple motion estimation) for motion-based segmentation into two groups: border placement schemes and region extraction schemes. While a border placement scheme looks for motion boundaries between regions that have different motion properties, a region extraction scheme looks for regions that maximize some motion-related homogeneity criterion. Though this classification is useful in understanding basic concepts to classify different motion segmentation methods, it does not include recent approaches such as methods that estimate motion and carry out segmentation simultaneously.

Different classifications that include these more recent methods, which also focus on optical flow-based methods in which we are particularly interested, have recently been proposed by several authors [5]. Although these authors may use different labels for the various categories of approaches, we believe that these approaches fall into the following three categories: simultaneous approaches, top-down approaches, and bottom-up approaches. The top-down approaches commonly start with optical flow that is estimated globally from a sequence of images. Then, the optical flow field is partitioned into several regions that have similar motion properties in each region, using a segmentation method [6]. In the top-down approaches, the optical flows, once estimated, are not updated, whereas in the simultaneous approaches, the optical flows are updated in an iterative framework and the image is simultaneously segmented based on the uniformity of optical flows. The optical flow calculations and motion-based segmentations carried out using the expectation maximization (EM) framework belong to the simultaneous approach category [7].

All of these motion segmentation methods are based on optical flow estimation methods that rely on the constant brightness assumption and motion smoothness constraint, which can easily be violated. Consequently, the segmentation results will be severely distorted in the situations mentioned above. In this paper, we present an improved motion segmentation method based on an optical flow estimation technique that is robust against illumination changes and a general clustering algorithm.

2. Optical Flow Estimation

In this paper, we propose a robust optical flow estimation method that reformulates the brightness constancy constraint of Gennert and Negahdaripour [9] within the robust statistical framework of Black and Anandan [10]. Using this new approach, we can simultaneously alleviate the problem of illumination changes and motion discontinuities [13]. The classical brightness constancy constraint $I(x+\delta x, y+\delta y, t+\delta t) = I(x,y,t)$ [11] is replaced by the following more general form:

$$I(x+\delta x, y+\delta y, t+\delta t) = M(x,y,t)I(x,y,t) + C(x,y,t) \tag{1}$$

in which $I(x,y,t)$ is the intensity of a pixel in an image at coordinates (x,y) and time t, and $M(x,y,t)$ and $C(x,y,t)$ are multiplicative and additive radiometric parameters, respectively. We can let $M = 1+\delta M$ and $C = \delta C$, since M and C are expected to change only slightly from 1 and 0, respectively. Furthermore, approximating the left-hand side of (1) using a Taylor expansion up to the first order and dividing both sides by δt yields

$$I_x u + I_y v + I_t - I_m - c = 0 \tag{2}$$

where $I_x = \lim_{\delta x \to 0} \frac{\delta I}{\delta x}$, $I_y = \lim_{\delta y \to 0} \frac{\delta I}{\delta y}$, $I_t = \lim_{\delta t \to 0} \frac{\delta I}{\delta t}$, $u = \lim_{\delta t \to 0} \frac{\delta x}{\delta t}$, $v = \lim_{\delta t \to 0} \frac{\delta y}{\delta t}$, $I_m = \lim_{\delta t \to 0} \frac{\delta M}{\delta t}$, and $c = \lim_{\delta t \to 0} \frac{\delta C}{\delta t}$. We estimate optical flow by minimizing the same objective function that is used in the method of Gennert and Negahdaripour [9], but employ the discretized smoothness constraint and the robust M-estimators that are used by Black and Anandan [10] as follows:

$$(u,v)^T = \arg min \iint \left(E_b + \lambda_s E_s + \lambda_m E_m + \lambda_c E_c\right) dxdy \tag{3}$$

where λ_s, λ_m, and λ_c are the relative weighting parameters, and

$$E_b = \rho_b\left(I_x u + I_y v + I_t - I_m - c, \sigma_b\right), \quad E_s = \sum_{n \in N}\left[\rho_s\left(u - u_n, \sigma_s\right) + \rho_s\left(v - v_n, \sigma_s\right)\right]$$
$$E_m = \sum_{n \in N} \rho_m\left(m - m_n, \sigma_m\right), \qquad E_c = \sum_{n \in N} \rho_c\left(c - c_n, \sigma_c\right) \tag{4}$$

in which $\rho(\cdot)$ is a robust M-estimator, and σ_b, σ_s, σ_m, and σ_c are scale parameters for each estimator. Variables u_n, v_n, m_n, and c_n are the horizontal velocity, vertical velocity, and the time derivatives of the multiplicative and additive radiometric parameters of pixels belonging to a neighborhood N, respectively. The Lorentzian function is chosen as estimator $\rho(\cdot)$, and the objective function is minimized using the graduated non-convexity continuation (GNC) method and a gradient-based Simultaneous over relaxation (SOR) method as presented in [10]. The recursive equations that are used in the SOR phase are given by

$$u^{(n+1)} = u^{(n)} - \omega \frac{1}{T(u^{(n)})} \left.\frac{\partial E}{\partial u}\right|_{u=u^{(n)}}, \qquad v^{(n+1)} = v^{(n)} - \omega \frac{1}{T(v^{(n)})} \left.\frac{\partial E}{\partial v}\right|_{v=v^{(n)}}$$
$$m^{(n+1)} = m^{(n)} - \omega \frac{1}{T(m^{(n)})} \left.\frac{\partial E}{\partial m}\right|_{m=m^{(n)}}, \qquad c^{(n+1)} = c^{(n)} - \omega \frac{1}{T(c^{(n)})} \left.\frac{\partial E}{\partial c}\right|_{c=c^{(n)}} \tag{5}$$

where $0 < \omega < 2$ is a relaxation parameter that controls the speed of convergence. The derivatives of E with respect to each variable and their upper bound T are as follows:

$$
\begin{aligned}
\frac{\partial E}{\partial u} &= \iint\left\{I_x\varphi_b\left(I_x u+I_y v+I_t-I_m-c\right)+\lambda_s\sum_{n\in N}\varphi_s\left(u-u_n\right)\right\}dxdy \\
\frac{\partial E}{\partial v} &= \iint\left\{I_y\varphi_b\left(I_x u+I_y v+I_t-I_m-c\right)+\lambda_s\sum_{n\in N}\varphi_s\left(v-v_n\right)\right\}dxdy \\
\frac{\partial E}{\partial m} &= \iint\left\{-I\varphi_b\left(I_x u+I_y v+I_t-I_m-c\right)+\lambda_m\sum_{n\in N}\varphi_m\left(m-m_n\right)\right\}dxdy \\
\frac{\partial E}{\partial c} &= \iint\left\{-\varphi_b\left(I_x u+I_y v+I_t-I_m-c\right)+\lambda_c\sum_{n\in N}\varphi_c\left(c-c_n\right)\right\}dxdy
\end{aligned} \tag{6}
$$

$$
T(u)=\frac{I_x^{\,2}}{\sigma_b^{\,2}}+\frac{4\lambda_s}{\sigma_s^{\,2}},\quad T(v)=\frac{I_y^{\,2}}{\sigma_b^{\,2}}+\frac{4\lambda_s}{\sigma_s^{\,2}},\quad T(m)=\frac{I^2}{\sigma_b^{\,2}}+\frac{4\lambda_m}{\sigma_m^{\,2}},\quad T(c)=\frac{1}{\sigma_b^{\,2}}+\frac{4\lambda_c}{\sigma_c^{\,2}} \tag{7}
$$

3. Motion Segmentation

Among the motion segmentation methods that are classified in Sec. 1, we chose the top-down method because of its simplicity and ability to show the effectiveness of our optical flow method. For the clustering step needed in this approach, we will group pixels together on the basis of similarity of motion direction. An alternative approach would consist of grouping pixels in velocity $(u-v)$ space directly. We believe that clustering directly with respect to motion direction yields superior results on account of the immunity gained vis-a-vis the magnitude of the optical flow vector. With regard to the specifics of how clustering is accomplished with respect to the motion direction, we have experimented with three different methods: the valley seeking method [12], the region growing method, and the split-and-merge method. However, we will show only the results using the split-and-merge method in this paper because there is little difference among their results. The split-and-merge algorithm works in a way that is the opposite of the region-growing method. The initial region, which, at the beginning, is the entire image, is divided into four regions if the average of the differences of the directions of motion of all pixels is greater than a threshold. This process is repeated for each one of the four regions until no more splits occur. After finishing this splitting process, the neighboring regions are merged if the average of the differences of their directions of motion is less than a threshold.

4. Experimental Results

To effectively show the robustness of our optical flow estimation method and the motion-based segmentation, we used the image sequence of moving cars shown in Fig. 1.

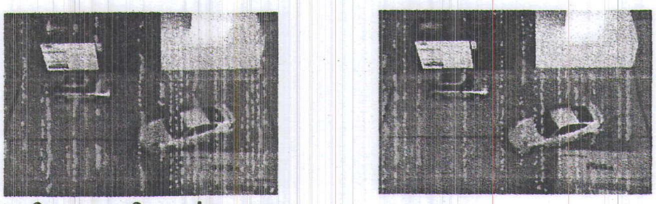
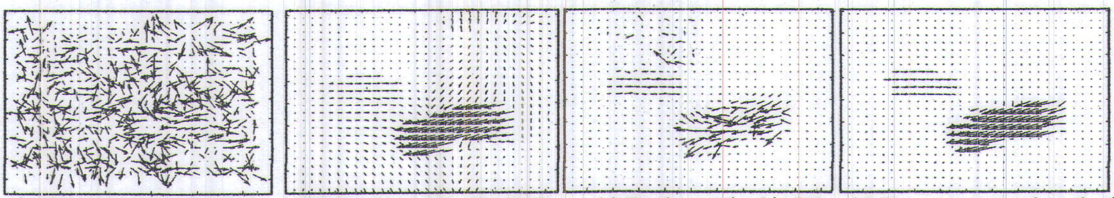


Fig. 1. Real test image frames of moving cars

Fig. 1 shows a sequence for moving cars, with illumination changes. Fig. 2 shows the optical flow results using three previously published methods and our new method for two image sequences. These results clearly show that the motion estimated by our method is closest to the actual motion of the moving objects, with the smallest effect from illumination change.



(a) By the method in [11] (b) By the method in [10] (c) By the method in [9] (d) By our proposed method

Fig. 2. Optical flow results for moving cars sequence

Fig. 3 shows the segmentation results from the optical flow estimation for the image sequence of moving cars. As we can see in these results, the motion segmentation based on our robust illumination invariant motion estimation method is more reliable for use in high-level processing in computer vision applications.

(a) By the method in [11] (b) By the method in [10] (c) By the method in [9] (d) By our proposed method

Fig. 3. Motion segmentation results for moving cars sequence

5. Conclusions

In this paper, we presented a new optical flow estimation method that is robust for large illumination changes and motion discontinuities by combining two existing methods into a single computation frame. A comparison with existing methods was made, and the superiority of our method was verified using synthesized and real images. We also presented a top-down motion segmentation approach using the split-and-merge algorithm based on our method of optical flow estimation, which is more reliable than the approaches based on other optical flow estimation methods.

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