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MOTION ANALYSIS IN VIDEO USING OPTICAL FLOW TECHNIQUES

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ABSTRACT: This paper presents optical flow estimation technique to estimate the motion vectors in each frame of the video sequence. By thresholding and performing morphological closing on the motion vectors, we produces binary feature images. Using these binary features the cars are located. A bounding Box is drawn around the cars that pass beneath the white line. The algorithm used for this is lucas kanade. Use of the threshold to reduce the noise in small movements between frames is analyzed. Higher the threshold ,the less small movements impact the optical flow calculation. Experiments are done to find the value that best achieves our results.

Keywords: Tracking, Thresholding, lucas-kanade, horn schunck, optical flow

1. INTRODUCTION

Motion analysis can be defined as the attempt to recover the motion parameters of a feature point in a video sequence, more specifically the parameters associated with the planar translation of a point. More formally, let $A = A_0, A_1, A_2, \ldots A_{j-1}$ denote the j images of a video sequence and $mi(x_i, y_i)$, $i = 0, \ldots j - 1$ denote a feature point in those frames. The task at hand is to determine a motion vector $d_i(d_{x,i}, d_{y,i})$ that best determines the position of the feature point in the next frame, $m_j(x_i, y_i)$, that is $m_j = m_{j-1} + d_j$. The object to be tracked is usually defined by the bounding box or the convex hull of the tracked feature points.

Feature based object tracking, although more prone to individual outliers and tracking drift, can be implemented very efficiently[4]. However most of the methods are sensitive to partial occlusions. An important point in object tracking is to determine and consequently track salient feature points in an image. Generally object tracking methods select pixels that have a distinctive characteristics with respect to their neighbors, such as brightness(most often), contrast, and so forth. Shi & Tomasi proposed a method for finding good features to track [2].

The Optical Flow block estimates the direction and speed of object motion from one image to another or from one video frame to another using either the Horn-Schunck or the Lucas-Kanade method [1], [3] . To compute the optical flow between two images, we must solve the following optical flow constraint equation:

$$I_x u + I_y v + I_t = 0 \tag{1}$$

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In this equation, the following values are represented: I_x, I_y, and I_t, are the spatiotemporal image brightness derivatives. u is the horizontal optical flow. v is the vertical optical flow. Because this equation is under constrained, there are several methods to solve for u and v, Horn-Schunck Method and Lucas-Kanade Method[5].

1.1. Horn-Schunck Method

By assuming that the optical flow is smooth over the entire image, the Horn-Schunck method computes an estimate of the velocity field, [u, v], that minimizes this equation

$$E = \iint (I_x u + I_y v + I_t)^2 \, dxdy + \alpha \iint \left[\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial v}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2 \right] dxdy \tag{2}$$

In this equation, $\frac{\partial u}{\partial x}$ and $\frac{\partial u}{\partial y}$ are the spatial derivatives of the optical velocity component u, and α scales the global smoothness term. The Horn-Schunck method minimizes the previous equation to obtain the velocity field, [u v], for each pixel in the image, which is given by the following equations

$$u^{k+1}_{x,y} = u^{-k}_{x,y} - \frac{I_x \left[I_x u^{-k}_{x,y} + I_y v^{-k}_{x,y} + I_t \right]}{\alpha^2 + I_x^2 + I_y^2} \tag{3}$$

$$v^{k+1}_{x,y} = v^{-k}_{x,y} - \frac{I_y \left[I_x u^{-k}_{x,y} + I_y v^{-k}_{x,y} + I_t \right]}{\alpha^2 I_x^2 + I_y^2} \tag{4}$$

In this equation, $\left[u^k_{x,y}, v^k_{x,y} \right]$ is the velocity estimate for the pixel at (x, y), and $\left[u^{-k}_{x,y}, v^{-k}_{x,y} \right]$ is the neighborhood average of. $\left[u_{x,y}^{k}, v_{x,y}^{k}\right]$ For k = 0, the initial velocity is 0. Compute I_x and I_y using the Sobel convolution kernel: [–1 –2 –1;0 0 0;1 2 –1], and its transposed form for each pixel in the first image. Compute I_t between images 1 and 2 using the [–1 1] kernel. Assume the previous velocity to be 0, and compute the average velocity for each pixel using [0 1 0;1 0 1;0 1 0] as a convolution kernel. Iteratively solve for u and v. The smoothness factor, α, is a positive constant. If the relative motion between the two video frames is large, enter a large positive scalar value for the Smoothness factor. If the relative motion is small, enter a small positive scalar value. You must experiment to find the smoothness factor that best suits your application. The iterative process stops when the velocity difference is below a certain threshold value. The block stops iterating as soon as one of these conditions is satisfied.

1.2. Lucas-Kanade Method

To solve the optical flow constraint equation for u and v, the Lucas-Kanade method divides the original image into smaller sections and assumes a constant velocity in each section. Then, it performs a weighted least-square fit of the optical flow constraint equation to a constant model for in each section, $[u, v]^T$, by minimizing the following equation

$$\sum_{x\in\Omega} W^2[I_x u + I_y v + I_t]^2 \tag{5}$$

Here, W is a window function that emphasizes the constraints at the center of each section. The solution to the minimization problem is given by the following equation:

$$\begin{bmatrix} \sum W^2 I_x^2 & \sum W^2 I_x I_y \\ \sum W^2 I_y I_x & \sum W^2 I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \sum W^2 I_x I_t \\ \sum W^2 I_y I_t \end{bmatrix} \tag{6}$$

Two methods are used, a difference filter or a derivative of a Gaussian filter. Find I_x, I_y, I_t, and u & v.

2. DIFFERENCE FILTER

The algorithm runs as follows. Compute I_x, and I_y, using the kernel [–1 8 0 –8 1]/12 and its transposed form. Compute I_t between images 1 and 2 using the [–1 1] kernel. Smooth the gradient components, I_x, I_y, and I_t using a separable and isotropic 5-by-5 element kernel whose effective 1-D coefficients are [1 4 6 4 1]/16. Solve the 2-by-2 linear equations for each pixel using the following method.

$$\text{If } A = \begin{bmatrix} a & b \\ b & c \end{bmatrix} = \begin{bmatrix} \sum W^2 I_x^2 & \sum W^2 I_x I_y \\ \sum W^2 I_y I_x & \sum W^2 I_y^2 \end{bmatrix} \tag{7}$$

Then the eigenvalues of A are

$$\lambda_1 = \frac{a+c}{2} \pm \frac{\sqrt{4b^2 + (a-c)^2}}{2} \tag{8}$$

for i = 1, 2

$$P = \frac{a+c}{2}$$

$$Q = \frac{\sqrt{4b^2 + (a-c)^2}}{2}$$

When eigenvalues are found, it compares them to the threshold, τ, The results fall into one of the following cases:

Case 1: $\lambda_1 \geq \tau$ and $\lambda_2 \geq \tau$ A is nonsingular, so solve the system of equations using Cramer's rule.

Case 2: $\lambda_1 \geq \tau$ and $\lambda_2 < \tau$ A is singular (noninvertible), so normalize the gradient flow to calculate u and v.

Case 3: $\lambda_1 < \tau$ and $\lambda_2 < \tau$ The optical flow, u and v, is 0.

3. DERIVATIVE OF GAUSSIAN

Compute I_x and I_y using the following steps. Use a Gaussian filter and the derivative of a Gaussian filter to smooth the image using spatial filtering. Compute I_t between images 1 and 2 using the following steps. Use the derivative of a Gaussian filter to perform temporal filtering. Smooth the gradient components, I_x, I_y, and I_t using a gradient smoothing filter. Solve the 2-by-2 linear equations for each pixel using the following method

$$\text{If } \quad A = \begin{bmatrix} a & b \\ b & c \end{bmatrix} = \begin{bmatrix} \sum W^2 I_x^2 & \sum W^2 I_x I_y \\ \sum W^2 I_y I_x & \sum W^2 I_y^2 \end{bmatrix} \tag{9}$$

Then the eigenvalues of A are

$$\lambda_i = \frac{a+c}{2} \pm \frac{\sqrt{4b^2 + (a-c)^2}}{2}$$

for i = 1,2

$$P = \frac{a+c}{2}$$

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Case 3: $\lambda_1 < \tau$ and $\lambda_2 \geq \tau$, The optical flow, u and v, is 0.

4. RESULTS

Using two different methods of velocity calculation, Horn-Schunck Method and Lucas kanade the object tracking results are shown.

Figure 1: Input Video

Figure 2: Threshold Video

Figure 3: Optical Flow Video

Figure 4: Tracked Qbjects Using Horn-Schunck Method

Figure 5: Tracked Objects Using Lucas Kanade Technique

5. CONCLUSION

The two methods of optical flow using partial derivative , Lucas-Kanade and Horn-Schunck method are studied. Lucas Kanade method is regarding image patches and an affine model for the flow field. Horn-Schunck method is optimizing a functional based on residuals from the brightness constancy constraint, and a particular regularization term expressing the expected smoothness of the flow field. Motion analysis & compression have developed as a major aspect of optical flow research. While the optical flow field is superficially similar to a dense motion field derived from the techniques of motion estimation, optical flow is the study of not only the determination of the optical flow field itself, but also of its use in estimating the three-dimensional nature and structure of the scene, as well as the 3D motion of objects and the observer relative to the scene.

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