

Optical Flow Algorithms

Jacky Baltes

University of Manitoba

Email: jacky@cs.umanitoba.ca

Web: www.cs.umanitoba.ca/~jacky

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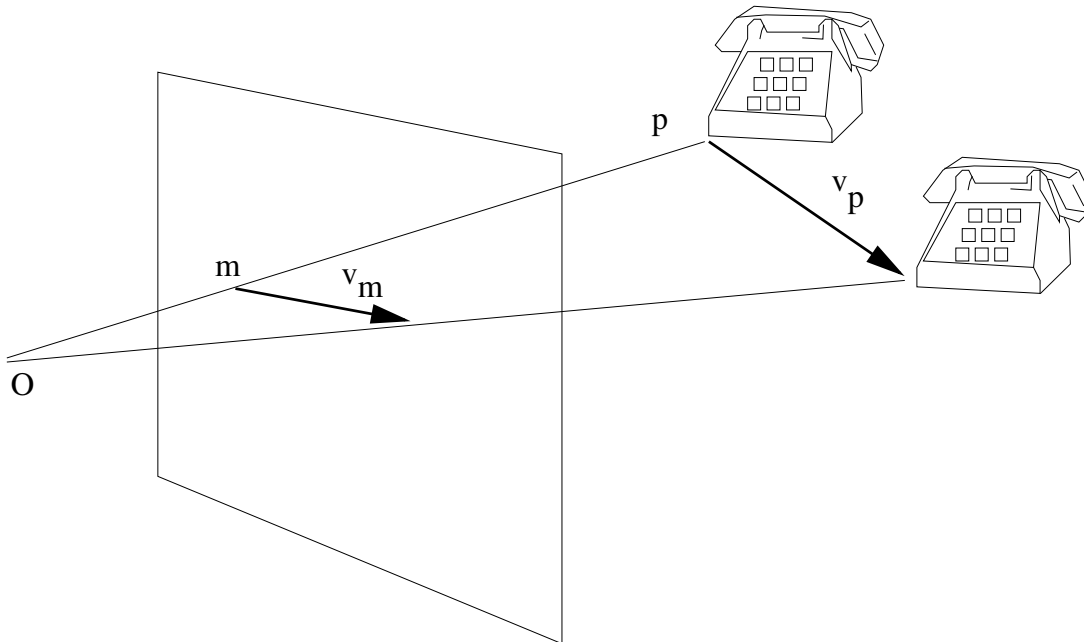
Motion Fields

- Motion is an important queue in computer vision. It is used in tracking, structure from motion, 3D reconstruction, video compression.
- Several issues
 1. 2D and 3D motion representations
 2. calculating 2D motion
 3. **inferring/estimating 3D motion**
 4. structure and motion

2D Motion Fields

- A velocity vector is associated with every point in the image
- Collection of these vectors is a 2D motion field

Image Projection



- P is a 3D point with coordinates $(X, Y, Z)^T$
- m is the image projection $(x, y)^T$
- $P = Z\hat{m}$
- differentiate with respect to time (to get velocities)

$$\frac{dp}{dt} = \frac{dZ}{dt} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} + Z \begin{bmatrix} dx/dt \\ dy/dt \\ 0 \end{bmatrix}$$

- that is

$$\dot{p} = \dot{Z}\hat{m} + Z\dot{\hat{m}}$$

2D Motion

- replace with velocities

$$V_p = (V_p^T k) \hat{m} + Z v_m$$

- solve for v_m

$$v_m = \frac{1}{Z} (V_p - (V_p^T k) \hat{m})$$

Optical Flow

- We can not observe the motion field directly
- We can observe images only and see how points in the image move
- Optical flow \neq motion field
- Example: a lighted sphere moves, light around the sphere moves
- Underlying assumption: optical flow is similar to motion field

Optical Flow Constraint Equation (OFCE)

- $I(x, y, t)$ is the image
- $m = (x, y)^T$ is a image pixel
- velocity of an image pixel

$$v_m = \dot{m} = [v_x, v_y]^T = \begin{bmatrix} dx/dt \\ dy/dt \end{bmatrix}$$

- Assumption: Intensity of pixel m is the same during dt

$$I(x + v_x dt, y + v_y dt, t + dt) = I(x, y, t)$$

Optical Flow Constraint Equation (OFCE)

- Use Taylor expansion to approximate differential

$$I(x, y, t) + \frac{\delta I}{\delta x} v_x dt + \frac{\delta I}{\delta y} v_y dt + \frac{\delta I}{\delta t} dt + \dots = I(x, y, t)$$

- Cancel $I(x, y, t)$, we have

$$\frac{\delta I}{\delta x} v_x + \frac{\delta I}{\delta y} v_y + \frac{\delta I}{\delta t} = 0$$

- this is the optical flow equation

$$\nabla I \cdot v_m + \frac{\delta I}{\delta t} = 0$$

- where $\nabla I = \left[\frac{\delta I}{\delta x}, \frac{\delta I}{\delta y} \right]^T$ is the image gradient at pixel m .

Image Gradient

- where $\nabla I = \left[\frac{\delta I}{\delta x}, \frac{\delta I}{\delta y} \right]^T$ is the image gradient at pixel m .
- This can be calculated from the image
- Also, $\frac{\delta I}{\delta t}$ can be calculated from the image
- However, we need to determine v_x and v_y and only have a single equation
- Aperture problem

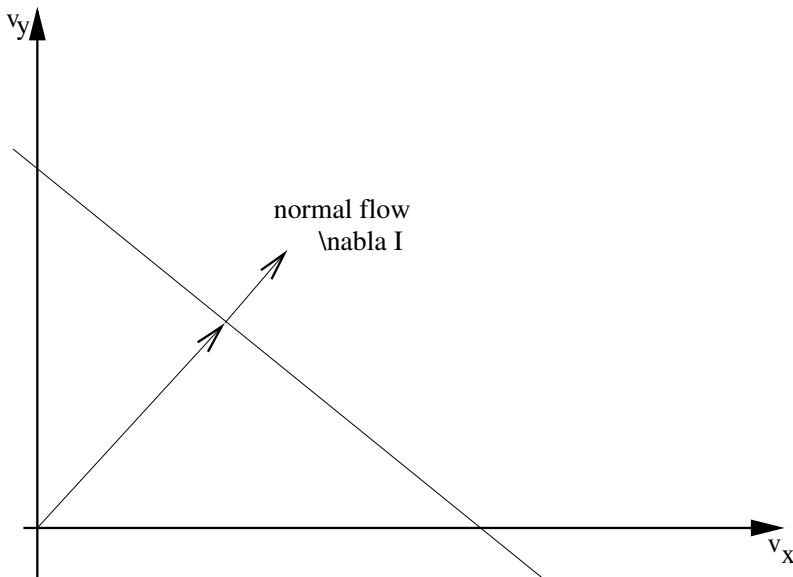


Image Gradient

- How to calculate the image gradient ∇I ?
- Later on, we need $\frac{\delta I}{\delta x}$ and $\frac{\delta I}{\delta y}$
- Use discrete approximation of the gradient from the image
- Simple: $\frac{\delta I(x,y)}{\delta x} = (I(x+1, y) - I(x-1, y))/2$
- Simple: $\frac{\delta I(x,y)}{\delta y} = (I(y+1, x) - I(y-1, x))/2$
- Implemented as convolution masks: $[-1, 0, +1]$

Image Gradient

- These derivatives are usually quite noisy, since they are based and emphasize the difference between neighboring pixels.
- Average a number of rows for $\frac{\delta I(x,y)}{\delta x}$
- Convolution mask

$$\begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix}$$

Common Convolution Masks

- Roberts $\begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ $\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$
- Prewitt $\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$ $\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$
- Sobel $\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ $\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$

Laplacian Methods

- Method for edge detection. Calculate gradient and threshold. In effect we are looking for extremas in I' .
- Another method for determining edges and the gradient it to look for 0 crossings in I'' .
- Need to apply a blur mask for noise reduction first, since otherwise much too noisy.
- Approximate 2nd order derivative in x direction

$$\nabla^2 I(x, y) = (\nabla I(x + 1, y) - \nabla I(x - 1, y))/2$$

- Some examples of Laplace operators

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \quad \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Horn Schunck Method

- A global method.
- Assumes that the optical flow field varies smoothly. Variation of the optical flow field can not be too big.
- Use a global smoothness constraint. Based on the gradient of the optical flow ∇v_x and ∇v_y .
- This technique is called regularization
- Isotropic stabilizer $\|\nabla v_x\|^2 + \|\nabla v_y\|^2$
- Measure of un-smoothness (Smoothness error)

$$e_s = \int \int (\|\nabla v_x\|^2 + \|\nabla v_y\|^2) dx dy$$

$$\int \int \left(\left(\frac{\delta v_x}{\delta x}\right)^2 + \left(\frac{\delta v_x}{\delta y}\right)^2 + \left(\frac{\delta v_y}{\delta x}\right)^2 + \left(\frac{\delta v_y}{\delta y}\right)^2 \right) dx dy$$

- Error of the optical flow $e_c = \int \int (\nabla I \cdot v_m + \frac{\delta I}{\delta t})^2 dx dy$
- Minimize the error $e = e_c + \lambda e_s$

$$e = e_c + \lambda e_s$$

$$= \int \int \left(\nabla I \cdot v_m + \frac{\delta I}{\delta t} \right)^2 + \lambda (\|\nabla v_x\|^2 + \|\nabla v_y\|^2) dx dy$$

Horn Schunck Method Discretization

- Given the four neighbors of a pixel, the smoothness function can be written as:

$$\begin{aligned} s(i, j) = & \frac{1}{4} [(v_x(i, j) - v_x(i - 1, j))^2 \\ & + (v_x(i + 1, j) - v_x(i, j))^2 \\ & + (v_x(i, j + 1) - v_x(i, j))^2 \\ & + (v_x(i, j) - v_x(i, j - 1))^2 \\ & + (v_y(i, j) - v_y(i - 1, j))^2 \\ & + (v_y(i + 1, j) - v_y(i, j))^2 \\ & + (v_y(i, j + 1) - v_y(i, j))^2 \\ & + (v_y(i, j) - v_y(i, j - 1))^2] \end{aligned}$$

Horn Schunck Method Discretization

- The error of the optical flow is

$$c(i, j) = \left[\frac{\delta I}{\delta x} v_x(i, j) + \frac{\delta I}{\delta y} v_y(i, j) + \frac{\delta I}{\delta t} \right]^2$$

- So, we want to minimize

$$\min E = \sum_i \sum_j [c(i, j) + \lambda s(i, j)]$$

Horn Schunck Method

- To minimize the error, we differentiate the error equation with respect to $v_x(i, j)$ and $v_y(i, j)$

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$$\frac{\delta e}{\delta v_x(i, j)} = 2 \left(\frac{\delta I}{\delta x} v_x(i, j) + \frac{\delta I}{\delta y} v_y(i, j) + \frac{\delta I}{\delta t} \right) \frac{\delta I}{\delta x} + 2\lambda(v_x(i, j) - \bar{v}_x(i, j)) = 0$$

$$\frac{\delta e}{\delta v_y(i, j)} = 2 \left(\frac{\delta I}{\delta x} v_x(i, j) + \frac{\delta I}{\delta y} v_y(i, j) + \frac{\delta I}{\delta t} \right) \frac{\delta I}{\delta y} + 2\lambda(v_y(i, j) - \bar{v}_y(i, j)) = 0$$

where \bar{v}_x and \bar{v}_y are local averages of v_x and v_y respectively.

Horn Schunck Method

- We can write

$$\left[\lambda + \left(\frac{\delta I}{\delta x} \right)^2 \right] v_x + \frac{\delta I}{\delta x} \frac{\delta I}{\delta y} v_y = \lambda \bar{v}_x - \frac{\delta I}{\delta x} \frac{\delta I}{\delta t}$$

$$\frac{\delta I}{\delta x} \frac{\delta I}{\delta y} v_x + \left[\lambda + \left(\frac{\delta I}{\delta x} \right)^2 \right] v_y = \lambda \bar{v}_y - \frac{\delta I}{\delta y} \frac{\delta I}{\delta t}$$

Horn Schunck Method

- Iterative scheme (Gauss-Seidel equations)

$$v_x^{k+1} = \bar{v}_x^k - \left[\frac{\left(\frac{\delta I}{\delta x}\right) \bar{v}_x^k + \left(\frac{\delta I}{\delta y}\right) \bar{v}_y^k + \frac{\delta I}{\delta t}}{\lambda + \left(\frac{\delta I}{\delta x}\right)^2 + \left(\frac{\delta I}{\delta y}\right)^2} \right] \frac{\delta I}{\delta x}$$

$$v_y^{k+1} = \bar{v}_y^k - \left[\frac{\left(\frac{\delta I}{\delta x}\right) \bar{v}_x^k + \left(\frac{\delta I}{\delta y}\right) \bar{v}_y^k + \frac{\delta I}{\delta t}}{\lambda + \left(\frac{\delta I}{\delta x}\right)^2 + \left(\frac{\delta I}{\delta y}\right)^2} \right] \frac{\delta I}{\delta y}$$

- More concisely: $\mathbf{v}^{k+1} = \bar{\mathbf{v}}^k - \alpha(\nabla \mathbf{I})$

Horn Schunck Method Implementation

- Usually use the following three masks to compute spatio

temporal differences $M_x = \frac{1}{4} \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix}$, $M_y =$

$$\frac{1}{4} \begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix}, M_t = \frac{1}{4} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

- Use the following equations to compute $\frac{\delta I}{\delta x}$, $\frac{\delta I}{\delta y}$, and $\frac{\delta I}{\delta t}$

$$\frac{\delta I}{\delta x} = M_x * (I_1 + I_2)$$

$$\frac{\delta I}{\delta y} = M_y * (I_1 + I_2)$$

$$\frac{\delta I}{\delta t} = M_t * (I_2 - I_1)$$