

sources of optical flow (relevant):

- relative motion between object & viewer
  - ↳ allows to infer spatial arrangements
- discontinuities in flow field can be used for segmentation
- motion recovery (objects xor self)
- shape

Violation: uniform sphere w/shading

- ① rotate sphere
- ② move light source.

Horn & Schunck version:

$$\nabla I \cdot X = -I_t$$

Component/  
Magnitude of movement in the direction of the brightness gradient equals

$$- \frac{I_t}{\|\nabla I\|_2}$$

cannot determine component in direction of iso-brightness contours.

$$\text{add smoothness constraint} \quad \min \lambda (\|\nabla u\|^2 + \|\nabla v\|^2)$$

⇒

$$\begin{aligned} & \|\nabla u\|^2 \\ & u_x^2 + u_y^2 \\ & \|\nabla v\|^2 \\ & \Rightarrow 2 \nabla u \cdot \nabla v \end{aligned}$$

$$L(X) = \iint [ (\nabla I \cdot X + I_t)^2 + \alpha^2 (\|\nabla u\|^2 + \|\nabla v\|^2) ] dx dy$$

⇒ compute 1st variation:

$$\frac{\delta L}{\delta X} \cdot \delta X = \iint [ 2(\nabla I \cdot X + I_t) \nabla I \cdot \delta X + \alpha^2 (2 \nabla u \cdot \delta u + 2 \nabla v \cdot \delta v) ] dx dy$$

$$= \iint [ 2(\nabla I \cdot X + I_t) \nabla I \cdot \delta X + 2\alpha^2 (\nabla u \cdot \nabla \delta u + \nabla v \cdot \nabla \delta v) ] dx dy$$

$\alpha^2$  indicates how much the current frame has been shifted from the previous frame.

In Matlab, it is the same equation to calculate optical flow as the one for optical flow.

After calculating optical flow, we can obtain the optical flow vector. The optical flow vector is obtained by convolution.

$\alpha^2 + I_x^2 + I_y^2$  is a matrix. It is a constant value for all pixels.

$I_x, I_y, I_t$  are matrices. They are constant for each pixel.

$I_x \alpha^2 + I_y \alpha^2 + I_t$  is a matrix. It is a constant value for each pixel.

$I_x \alpha^2, I_y \alpha^2, I_t$  are computed matrices.

Quiver plot shows the direction and magnitude of optical flow.

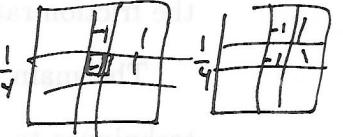
Need two images,  $\alpha^2$  parameter, and 4 iterations.

$$\begin{array}{|c|c|} \hline -1 & -1 \\ \hline 1 & 1 \\ \hline \end{array}$$

Only one for loop in MATLAB optical flow function.

$$\begin{array}{|c|c|c|} \hline 0 & -1 & 1 \\ \hline 0 & -1 & 1 \\ \hline 0 & 0 & 0 \\ \hline \end{array}$$

Can use basic  $I_x, I_y, I_t$  or can get fancier.



$$HFS: I_x = \frac{1}{4} (I(i,j+1,k) - I(i,j,k) + I(i+1,j+1,k) - I(i+1,j,k))$$

$$+ I(i,j+1,k+1) - I(i,j,k+1)) \Rightarrow I(i,j,k) + I(i+1,j+1,k+1) - I(i+1,j+1,k)$$

$I_y$  is similar.

$$I_t = \frac{1}{4} (I(i,j,k+1) - I(i,j,k) + I(i+1,j,k+1) - I(i+1,j,k))$$

$$+ I(i,j+1,k+1) - I(i,j+1,k) + I(i+1,j+1,k+1) - I(i+1,j+1,k))$$



average of forward Euler in space and time.

$$(a_{11}u + a_{12}v) + (a_{21}u + a_{22}v) \frac{\partial}{\partial u} = (\nabla I \cdot x + I_t) \quad \text{and} \quad ((I_t - I_x u - I_y v) \frac{\partial}{\partial v} = (\nabla I \cdot x + I_t) \quad \text{and}$$

by parts

RNA structure  
monomers structure

$$\int \Delta u \cdot \delta u \, dx \, dy - \iint \Delta u \cdot \delta u$$

$$\frac{\delta L}{\delta x} \cdot \delta x = \iint [ z(\nabla I \cdot x + I_t) \nabla I \cdot \delta x - 2\alpha^2 (\Delta u, \Delta v) \cdot \delta x ] \, dx \, dy$$

$$= \iint [ z(\nabla I \cdot x + I_t) \nabla I - 2\alpha^2 (\Delta u, \Delta v) ] \cdot \delta x \, dx \, dy$$

two components in integrand must vanish:

$$z(\nabla I \cdot x + I_t) \cdot I_x - 2\alpha^2 \Delta u = 0$$

$$z(\nabla I \cdot x + I_t) \cdot I_y - 2\alpha^2 \Delta v = 0$$

$\Rightarrow$

$$I_x^2 u + I_y v = \alpha^2 \Delta u - I_x I_t$$

$$I_x I_y u + I_y^2 v = \alpha^2 \Delta v - I_y I_t$$

$\Rightarrow$  def. of Laplacian in  $\bar{u}, \bar{v}$

$$(\alpha^2 + I_x^2) u + I_x I_y v = \alpha^2 \bar{u} - I_x I_t$$

$$I_x I_y u + (\alpha^2 + I_y^2) v = \alpha^2 \bar{v} - I_y I_t$$

$\Rightarrow$

$$\begin{bmatrix} \alpha^2 + I_x^2 & I_x I_y \\ I_x I_y & \alpha^2 + I_y^2 \end{bmatrix} \begin{Bmatrix} u \\ v \end{Bmatrix} = \begin{Bmatrix} \alpha^2 \bar{u} - I_x I_t \\ \alpha^2 \bar{v} - I_y I_t \end{Bmatrix}$$

$$\alpha^2 + I_x^2 - I_x^2 I_y^2$$

$$\alpha^2 (\alpha^2 + I_x^2 + I_y^2)$$

define  $\Delta u, \Delta v$

$$\alpha^2 (\alpha^2 + I_x^2 + I_y^2) \begin{Bmatrix} u \\ v \end{Bmatrix} = \begin{bmatrix} \alpha^2 + I_y^2 & -I_x I_y \\ -I_x I_y & \alpha^2 + I_x^2 \end{bmatrix} \begin{Bmatrix} \alpha^2 \bar{u} - I_x I_t \\ \alpha^2 \bar{v} - I_y I_t \end{Bmatrix}$$

$\Rightarrow$

$$\cancel{\alpha^2 + I_x^2 - I_x^2 I_y^2} \quad u = (\alpha^2 + I_x^2 + I_y^2)^{-1} [ (\alpha^2 + I_y^2) \bar{u} - I_x I_y \bar{u} - I_x I_t ]$$

$$v = (\alpha^2 + I_x^2 + I_y^2)^{-1} [ (\alpha^2 + I_x^2) \bar{v} - I_x I_y \bar{u} - I_y I_t ]$$

⇒ ALTERNATIVELY

(61)

$$(\alpha^2 + I_x^2 + I_y^2)(\bar{u} - \bar{u}) = -$$

and since we want to minimize the right hand side we have  
 $u = \bar{u} - (\alpha^2 + I_x^2 + I_y^2)^{-1} [I_x(I_x\bar{u} + I_y\bar{v} + I_t)]$   
 $v = \bar{v} - (\alpha^2 + I_x^2 + I_y^2)^{-1} [I_y(I_x\bar{u} + I_y\bar{v} + I_t)]$

(61)

this is the solution.

but since we need to find these  $u$ , we use gradient descent.

called Gauss-Seidel is used for linear systems.

(61)

Note that solution to  $u$  is linear in  $\bar{u}$  and  $\bar{v}$

⇒

if

$$x = Ay$$

$$r_k = (x_k - Ax_k)$$

(61)

solution given by

$\uparrow$  this is defect.

$$Ax = 0$$

$$Ax_k = r_k$$

(61)

$$x_{k+1} = x_k - \gamma r_k = x_k - (x_k - Ax_k) = A\gamma_k$$

but then  $\gamma$  changes implicitly

$$r_{k+1} = x_{k+1} - Ax_{k+1}$$

⇒

$$x_{k+1} = A\gamma_k$$

and construct to next step of "reset" has value of  $\gamma$  because new nonzero values in  $A$  add to  $\gamma$  from last step of update. So in next step of update  $\gamma$  is updated to reflect new non-zero values in  $A$ .

$$u^{n+1} = \bar{u}^n - I_x(\alpha^2 + I_x^2 + I_y^2)^{-1}(I_x\bar{u}^n + I_y\bar{v}^n + I_t)$$

$$v^{n+1} = \bar{v}^n - I_y(\alpha^2 + I_x^2 + I_y^2)^{-1}(I_x\bar{u}^n + I_y\bar{v}^n + I_t)$$

in this step shifting iteration is to truncatedly escape from old  $\gamma$  and in

order to exit to next step a boundary of size tolerance-one condition is goals given before doing round of truncation escape from old to truncated current  $\gamma$  and truncated boundary

In optical flow case, we have

$$Ax = b$$

$\Rightarrow$

$$(I + N)x = b$$

$$N = I - A$$

$\Rightarrow$

$$Ix_{n+1} = b + Nx_n$$

↑                   ↑  
 image only terms      OFC + smoothness

But, we can do this differently.

$$u^{n+1} = \bar{u}^n - \frac{Ix\bar{u}^n + Iy\bar{v}^n + I_t}{1 + \alpha^2(I_x^2 + I_y^2)} \quad I_x$$

↓ i.e. class

$$v^{n+1} = \bar{v}^n - \frac{Ix\bar{u}^n + Iy\bar{v}^n + I_t}{1 + \alpha^2(I_x^2 + I_y^2)} \quad I_y$$

↓ i.e. class



in this other case, we have

$$\mathcal{E} = \alpha^2 \mathcal{E}_{OFC} + \mathcal{E}_S$$

\* discuss boundary conditions!  
 $(u_x, u_y)^\top \cdot \hat{n} = 0 \quad (v_x, v_y)^\top \cdot \hat{n} = 0$

- the two algorithms are equivalent, but can differ.

need to verify this with my code.

did I program both?

optical flow field:

velocity field ~~for~~ defined on image domain that transforms one image to another

→ not uniquely determined (projection equations one problem)

**motion field:**

projection onto the image of three-dimensional vectors

other possible sources of error:

specular effects

shadows

insufficient texturing

occlusion

define a vector field?

$X : \mathbb{R}^2 \rightarrow \mathbb{R}^2$

↑  
at every point in image  
defines a vector describing particle motion

if we integrate the vector field

$$\dot{x} = X(x), \quad x(0) = x_0$$

then we get particle trajectories for various  $x_0$ . Call them  $\Phi_{0,t}^X(x_0)$

but, at an edge where there is more image variation, the situation is less ambiguous.

Furthermore, all particles at an edge move with locally consistent velocities.

what's one way to impose local consistency?

e.g. restrict local variation

(v) isotropic smoothing e.g. reg smoothness

- choose weight function such that it is zero at boundaries and non-zero in the interior. e.g.  $\frac{1}{\sqrt{1 + \alpha^2}}$

isotropic diffusion

- choose weight function such that it is zero at boundaries and non-zero in the interior. e.g.  $\frac{1}{\sqrt{1 + \alpha^2}}$

$$(1) \quad (0.5, 0.5, 0) = (0.5, 0.5, 0) + (0.5, 0, 0) = (0.5, 0.5, 0)$$

choose weight function such that it is zero at boundaries and non-zero in the interior. e.g.  $\frac{1}{\sqrt{1 + \alpha^2}}$

- choose weight function such that it is zero at boundaries and non-zero in the interior. e.g.  $\frac{1}{\sqrt{1 + \alpha^2}}$

$$(2) \quad \left( \frac{x}{\Delta} \right) \frac{\frac{w}{\Delta} + \frac{w}{\Delta}}{\Delta} \sum_{i=1}^{11} = (x), \text{reg}$$

$$(3) \quad \left( \frac{x}{\Delta} \right) \frac{\frac{w}{\Delta} + \frac{w}{\Delta}}{\Delta} \sum_{i=1}^{11} = (x), \text{reg}$$

the resulting  $x$  is the final result of the isotropic diffusion.

$$(4) \quad (0.5, 0.5, 0) = (0.5, 0.5, 0) - (0.5, 0, 0) = (0.5, 0.5, 0)$$

(5)

$$(6) \quad (0.5, 0, 0) = (0.5, 0.5, 0) - (0.5, 0.5, 0) = (0.5, 0, 0)$$

choose weight function such that it is zero at boundaries and non-zero in the interior. e.g.  $\frac{1}{\sqrt{1 + \alpha^2}}$

Suppose an imaged particle is moving, then it satisfies the following equation

$$I(\Phi_{0,t}^X(x), t) = I(x, 0)$$

assuming nothing else funny is going on

called "Brightness Constancy Assumption"



time derivative vanishes

$$\frac{d}{dt} I(\Phi_{0,t}^X(x), t) = \frac{\partial}{\partial t} I(x, 0)$$



$$\nabla I \cdot \frac{\partial}{\partial t} \Phi_{0,t}^X + \frac{\partial I}{\partial t} = 0$$



$$\nabla I \cdot X + \frac{\partial I}{\partial t} = 0$$



$$\frac{\partial I}{\partial x} u + \frac{\partial I}{\partial y} v + \frac{\partial I}{\partial t} = 0$$

optical flow constraint  
equation (ofc)

Problems one constraint (ofc) versus two unknowns ( $u, v$ ).



multiple solutions possible.

$\hookrightarrow$  equicontour



if intensity is uniform in a region, then vector field is ambiguous  
but should also be "uniform" in some sense.

## Iterative Methods.

$$Ax = b$$



$(S+N)x = b$  invertible.



$$Sx = b + Nx$$



$$x = S^{-1}(b + Nx)$$

$$x_{n+1} = S^{-1}(b + Nx_n)$$

$$= S^{-1}b + S^{-1}Nx_n$$

in our case, structure of optical flow lets us solve this pixel by pixel,

since  $S$  is the diagonal part of  $A$  and  $N$  is the off-diagonal part.

$$x_{k+1} = b + (S+N)x_k ?$$

Richardson iteration

$$S = I, \quad N = (I - A)$$

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$$Ax^* = b$$

$$\Rightarrow \delta x^* = b + Nx^*$$

$$x^* = S^{-1}b + S^{-1}Nx^*$$

$$X = X - e$$

$$r = Ax - b$$

$$r = Ax - Ax^* = Ae$$

↑ true solution



$$x = A^{-1}r = x^*$$

↓ don't have

$$e_k = Ax_k - Ax^*$$

$$e_{k+1} = Ax_{k+1} - Ax^*$$

$$= AS^{-1}(b - Nx_k) - Ax^*$$

$$= AS^{-1}(b) - b + AS^{-1}Nx_k$$

=

$$e_{k+1} = x_{k+1} - x^* = S^{-1}b + S^{-1}Nx_k - x^*$$

$$= +S^{-1}Nx_k = S^{-1}N e_k$$

$$= S^{-1}N e_k$$

all good, so long as  $\|S^{-1}N\| < 1$

⇒ eig. of  $S^{-1}N$  are less than unity

even will reduce w/ each iteration.

OFC +  $L_2$  smoothness → iterative method.

## GRADIENT DESCENT OPTICAL FLOW:

instead of solving for the minimal solution, one can use gradient descent to arrive at it,

$$\frac{\delta u}{\delta t} = -[(\nabla I \cdot X + I_t) I_x - \alpha^2 \Delta u]$$

$$\frac{\delta v}{\delta t} = -[(\nabla I \cdot X + I_t) I_y - \alpha^2 \Delta v]$$

$\Rightarrow$

$$\frac{u^{n+1} - u^n}{\Delta t} = (\nabla I \cdot X + I_t) I_x - \alpha^2 \Delta u$$

$\Rightarrow$

$$u^{n+1} = u^n - \Delta t [(\nabla I \cdot X + I_t) I_x - \alpha^2 \Delta u] - 4u$$

$$v^{n+1} = v^n - \Delta t [(\nabla I \cdot X + I_t) I_y - \alpha^2 \Delta v]$$

$$\Delta u = u^{n+1} + u^{n+1} + u^{n+1} + u^{n+1}$$

$$v^{n+1} = v^n - \Delta t [(\nabla I \cdot X + I_t) I_y - \alpha^2 \Delta v]$$