# Motion and Optical Flow

Introduction to Computational Photography: EECS 395/495

Northwestern University

### Motion and Optical Flow

Method to estimate apparent motion of scene objects from a sequence of images.

### Topics:

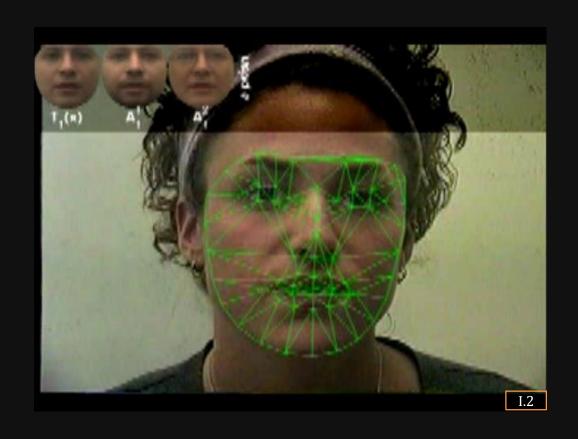
- (1) Motion Field
- (2) Optical Flow
- (3) Optical Flow Constraints
- (4) Optical Flow Algorithms

## Where is Motion Estimation Used?



Finding Velocities of Vehicles

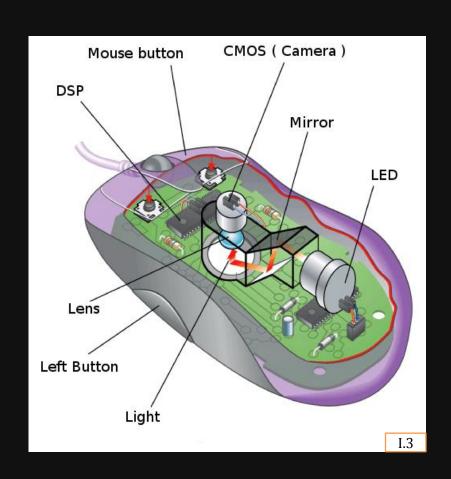
## Where is Motion Estimation Used?



Tracking of Facial Features

### Where is Motion Estimation Used?





**Estimating Mouse Movements** 

### **Motion Field**

Image velocity of a point that is moving in the scene

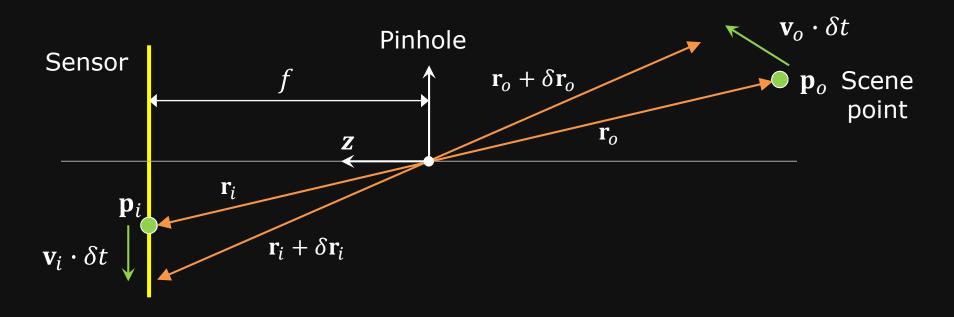


Image Point Velocity: 
$$\mathbf{v}_i = \frac{d\mathbf{r}_i}{dt}$$
 Scene Point Velocity:  $\mathbf{v}_o = \frac{d\mathbf{r}_o}{dt}$  (Motion Field)

### **Motion Field**

Image velocity of a point that is moving in the scene

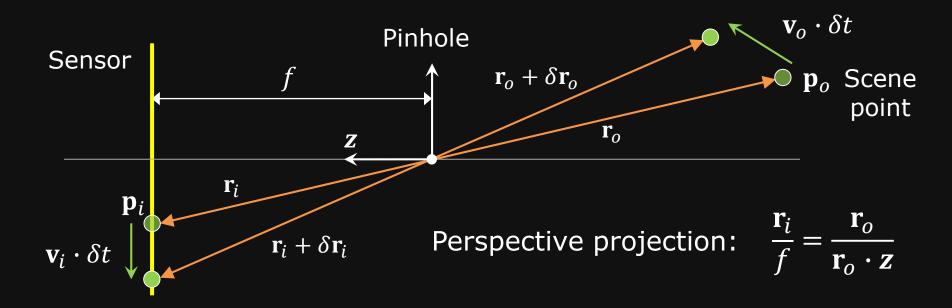


Image Point Velocity: 
$$\mathbf{v}_i = \frac{d\mathbf{r}_i}{dt} = f\frac{(\mathbf{r}_o \cdot \mathbf{z})\mathbf{v}_0 - (\mathbf{v}_o \cdot \mathbf{z})\mathbf{r}_0}{(\mathbf{r}_o \cdot \mathbf{z})^2}$$

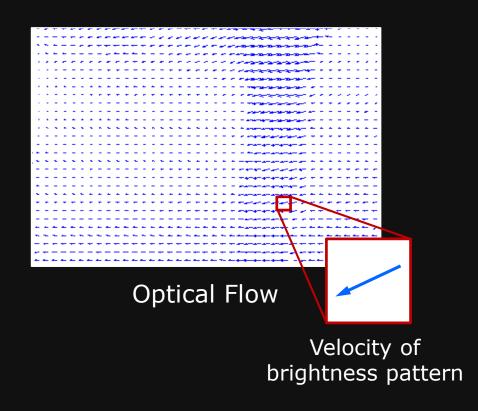
(Motion Field)
$$\mathbf{v}_i = f\frac{(\mathbf{r}_o \times \mathbf{v}_0) \times \mathbf{z}}{(\mathbf{r}_o \cdot \mathbf{z})^2}$$

## **Optical Flow**

### Motion of brightness patterns in the image

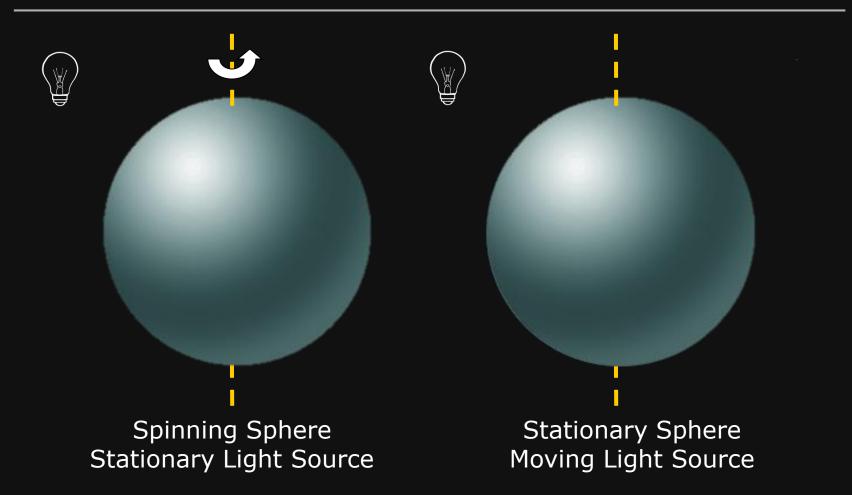


Image Sequence (2 frames)



Ideally, Optical Flow = Motion Field

### When is Optical Flow $\neq$ Motion Field?



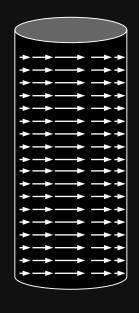
Motion Field exists
But no Optical Flow

No Motion Field exists
But There is Optical Flow

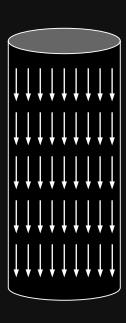
### When is Optical Flow ≠ Motion Field?



Barber Pole Illusion

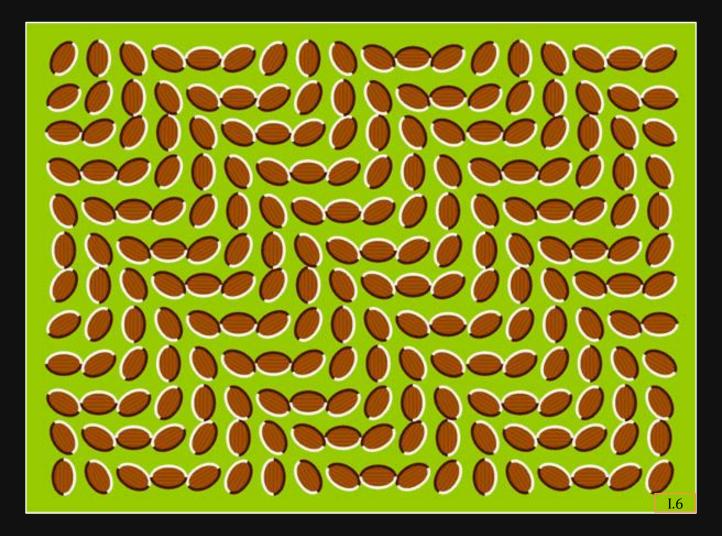


Motion Field



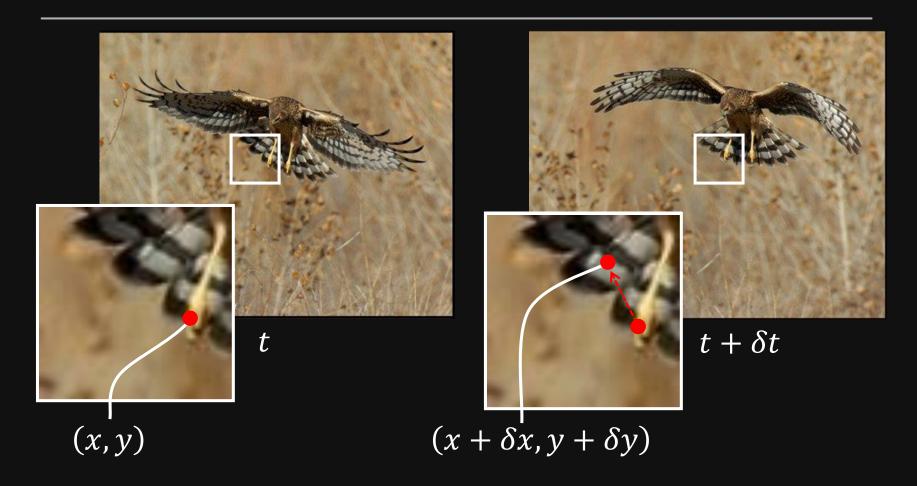
**Optical Flow** 

### Perceived Motion Without Motion



Donguri Wave Illusion

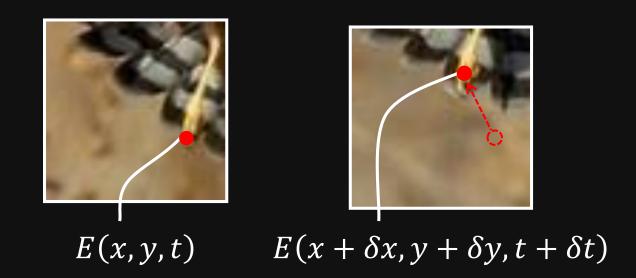
## **Optical Flow**



Displacement:  $(\delta x, \delta y)$ 

Optical Flow:  $(u, v) = \left(\frac{\delta x}{\delta t}, \frac{\delta y}{\delta t}\right)$ 

### **Optical Flow Constraints**

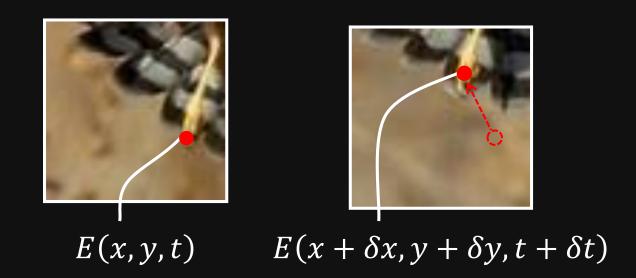


#### Assumption #1:

Brightness of an image point remains constant over time

$$E(x + \delta x, y + \delta y, t + \delta t) = E(x, y, t)$$

### **Optical Flow Constraints**



#### Assumption #2:

Displacement  $(\delta x, \delta y)$  and time step  $\delta t$  are small

### Taylor Series Expansion

Expand a function as an infinite sum of its derivatives

$$f(x + \delta x) = f(x) + \frac{\partial f}{\partial x} \delta x + \frac{\partial^2 f}{\partial x^2} \frac{\delta x^2}{2!} + \dots + \frac{\partial^n f}{\partial x^n} \frac{\delta x^n}{n!}$$

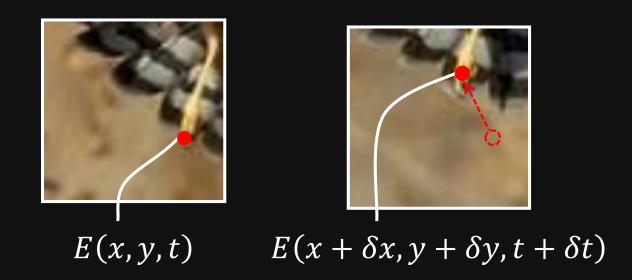
If  $\delta x$  is small:

$$f(x + \delta x) = f(x) + \frac{\partial f}{\partial x} \delta x + O(\delta x^2)$$
 Almost Zero

For a function of three variables with small  $\delta x$ ,  $\delta y$ ,  $\delta t$ :

$$f(x + \delta x, y + \delta y, t + \delta t) \approx f(x, y, t) + \frac{\partial f}{\partial x} \delta x + \frac{\partial f}{\partial y} \delta y + \frac{\partial f}{\partial t} \delta t$$

### **Optical Flow Constraints**



#### Assumption #2:

Displacement and time step are small

$$E(x + \delta x, y + \delta y, t + \delta t) = E(x, y, t) + \frac{\partial E}{\partial x} \delta x + \frac{\partial E}{\partial y} \delta y + \frac{\partial E}{\partial t} \delta t$$

$$E(x + \delta x, y + \delta y, t + \delta t) = E(x, y, t) + E_x \delta x + E_y \delta y + E_t \delta t$$

## Optical Flow Constraint Equation

$$E(x + \delta x, y + \delta y, t + \delta t) = E(x, y, t)$$
(1)

$$E(x + \delta x, y + \delta y, t + \delta t) = E(x, y, t) + E_x \delta x + E_y \delta y + E_t \delta t$$
-----(2)

Subtract (1) from (2): 
$$E_x \delta x + E_y \delta y + E_t \delta t = 0$$

Divide by 
$$\delta t$$
 and take limit as  $\delta t \to 0$ :  $E_x \frac{\partial x}{\partial t} + E_y \frac{\partial y}{\partial t} + E_t = 0$ 

Constraint Equation: 
$$E_x u + E_y v + E_t = 0$$

 $(E_x, E_y, E_t)$  can be easily computed from two frames (later).

### Geometric Interpretation

For any point (x, y) in the image, its optical flow (u, v) lies on the line:

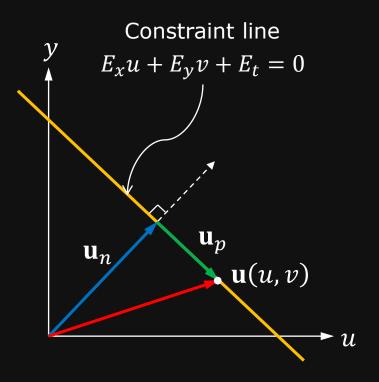
$$E_{\chi}u + E_{\chi}v + E_t = 0$$

Optical Flow can be split into two components.

$$\mathbf{u} = \mathbf{u}_n + \mathbf{u}_p$$

 $\mathbf{u}_n$ : Normal Flow

 $\mathbf{u}_p$ : Parallel Flow



### Normal Flow

#### Direction of Normal Flow:

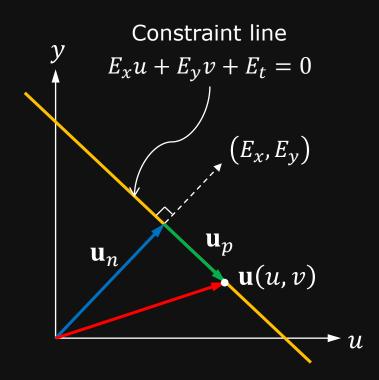
Unit vector perpendicular to the constraint line:

$$\widehat{\mathbf{u}}_n = \frac{\left(E_x, E_y\right)}{\sqrt{E_x^2 + E_y^2}}$$

#### Magnitude of Normal Flow:

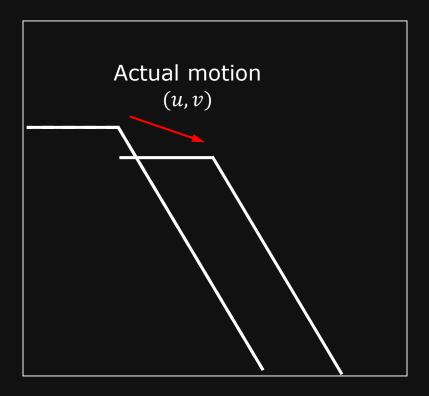
Distance of origin from the constraint line:

$$|\mathbf{u}_n| = \frac{|E_t|}{\sqrt{E_x^2 + E_y^2}}$$

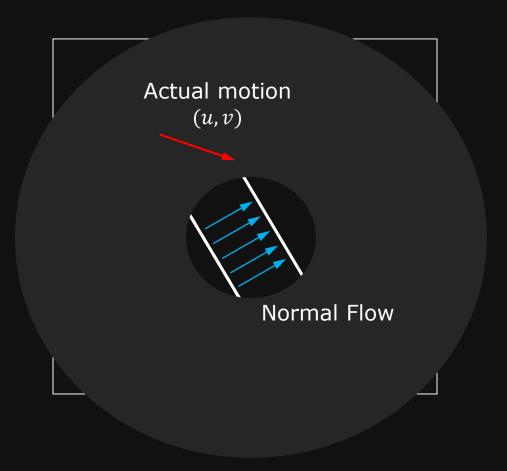


$$\mathbf{u}_n = \frac{|E_t|}{\left(E_x^2 + E_y^2\right)} \left(E_x, E_y\right)$$

# Aperture Problem



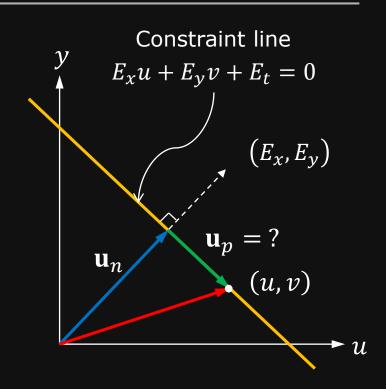
# Aperture Problem



Locally, we can only determine normal flow!

### Optical Flow is Under Constrained

We cannot determine the optical flow component  $\mathbf{u}_p$  parallel to the constraint line.



Finding optical flow (u, v) is under-constrained just like finding gradient (p, q) is under-constrained in shape from shading.

We need additional assumptions

### **Optical Flow Constraint**

Requirement: Optical Flow must satisfy the constraint

equation:  $E_x u + E_y v + E_t = 0$ 

Minimize:

$$e_c = \iint (E_x u + E_y v + E_t)^2 dx \, dy$$
Image

Aim: Penalize errors/departure from the constraint equation.

### **Smoothness Constraint**

Assumption: Motion field and hence optical flow (u, v) varies "smoothly" in an image.

#### Minimize:

$$e_S = \iint (u_x^2 + u_y^2) + (v_x^2 + v_y^2) dx dy$$
Image

where: 
$$u_x = \frac{\partial u}{\partial x}$$
,  $u_y = \frac{\partial u}{\partial y}$ ,  $v_x = \frac{\partial v}{\partial x}$  and  $v_y = \frac{\partial v}{\partial y}$ 

Aim: Penalize rapid changes in u and v.

# Computing Optical Flow

Find optical flow (u, v) at each pixel that minimizes:

$$e = e_s + \lambda e_c$$

#### where:

 $e_s$ : Smoothness Error

 $e_c$ : Optical Flow Error

 $\lambda$ : Weighting factor

Optical Flow Constraint Error at point (i, j)

$$e_{c_{i,j}} = \left(E_{x_{i,j}}u_{i,j} + E_{y_{i,j}}v_{i,j} + E_{t_{i,j}}\right)^2$$

Smoothness Error at point (i, j)

$$e_{s_{i,j}} = \frac{1}{4} \left( \left( u_{i+1,j} - u_{i,j} \right)^2 + \left( u_{i,j+1} - u_{i,j} \right)^2 \right)$$

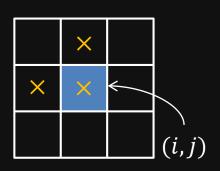
Find  $(u_{i,j}, v_{i,j})$  for all (i,j) that minimize:

$$e = \sum_{i} \sum_{j} \left( e_{s_{i,j}} + \lambda e_{c_{i,j}} \right)$$

If 
$$(u_{k,l}, v_{k,l})$$
 minimizes  $e$ , then  $\frac{\partial e}{\partial u_{k,l}} = 0$  and  $\frac{\partial e}{\partial v_{k,l}} = 0$ 

Given an image of size  $N \times N$ , there are  $2N^2$  unknowns.  $(N^2 \, u_{i,j}{}'\! s)$  and  $N^2 \, v_{i,j}{}'\! s)$ 

However, note that each  $u_{i,j}$  and  $v_{i,j}$  appears in the terms of 3 pixels.



If 
$$(u_{k,l}, v_{k,l})$$
 minimizes  $e$ , then  $\frac{\partial e}{\partial u_{k,l}} = 0$  and  $\frac{\partial e}{\partial v_{k,l}} = 0$ 

Therefore:

Eq 1: 
$$\frac{\partial e}{\partial u_{k,l}} = 2(u_{k,l} - \bar{u}_{k,l}) - 2E_{x_{k,l}}(E_{x_{k,l}}u_{k,l} + E_{y_{k,l}}v_{k,l} + E_{t_{k,l}}) = 0$$

Eq 2: 
$$\frac{\partial e}{\partial v_{k,l}} = 2(v_{k,l} - \bar{v}_{k,l}) - 2E_{y_{k,l}}(E_{x_{k,l}}u_{k,l} + E_{y_{k,l}}v_{k,l} + E_{t_{k,l}}) = 0$$

where  $\bar{u}_{i,j}$  and  $\bar{v}_{i,j}$  are local averages.

$$\bar{u}_{i,j} = \frac{1}{4} (u_{i+1,j} + u_{i-1,j} + u_{i,j+1} + u_{i,j-1})$$

$$\bar{v}_{i,j} = \frac{1}{4} (v_{i+1,j} + v_{i-1,j} + v_{i,j+1} + v_{i,j-1})$$

If 
$$(u_{k,l}, v_{k,l})$$
 minimizes  $e$ , then  $\frac{\partial e}{\partial u_{k,l}} = 0$  and  $\frac{\partial e}{\partial v_{k,l}} = 0$ 

#### Therefore:

Eq 1: 
$$\frac{\partial e}{\partial u_{k,l}} = 2(u_{k,l} - \bar{u}_{k,l}) - 2E_{x_{k,l}}(E_{x_{k,l}}u_{k,l} + E_{y_{k,l}}v_{k,l} + E_{t_{k,l}}) = 0$$

Eq 2: 
$$\frac{\partial e}{\partial v_{k,l}} = 2(v_{k,l} - \bar{v}_{k,l}) - 2E_{y_{k,l}}(E_{x_{k,l}}u_{k,l} + E_{y_{k,l}}v_{k,l} + E_{t_{k,l}}) = 0$$

Moving all  $u_{k,l}$ 's and  $v_{k,l}$ 's to one side, we get...

### Iterative Solution of (u, v)

#### **Update Rule:**

(No Need to Memorize)

$$u_{k,l}^{(n+1)} = \bar{u}_{k,l}^{(n)} + \frac{E_{x_{k,l}} \bar{u}_{k,l}^{(n)} + E_{y_{k,l}} \bar{v}_{k,l}^{(n)} + E_{t_{k,l}}}{1 + \lambda \left[ \left( E_{x_{k,l}} \right)^2 + \left( E_{y_{k,l}} \right)^2 \right]} E_{x_{k,l}}$$

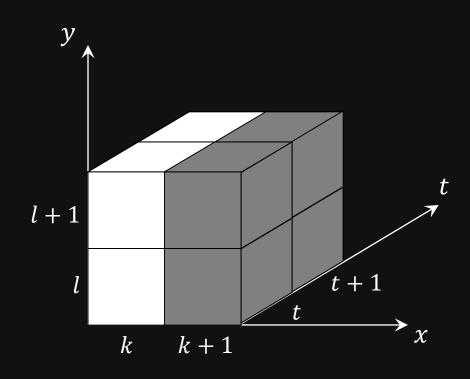
$$v_{k,l}^{(n+1)} = \bar{v}_{k,l}^{(n)} + \frac{E_{x_{k,l}} \bar{u}_{k,l}^{(n)} + E_{y_{k,l}} \bar{v}_{k,l}^{(n)} + E_{t_{k,l}}}{1 + \lambda \left[ \left( E_{x_{k,l}} \right)^2 + \left( E_{y_{k,l}} \right)^2 \right]} E_{y_{k,l}}$$

where: n is iteration index

Initialize 
$$u_{k,l}^{(0)} = 0$$
 and  $v_{k,l}^{(0)} = 0$ 

 $E_{\mathbf{x}_{k,l}}$ ,  $E_{\mathbf{y}_{k,l}}$ ,  $E_{\mathbf{t}_{k,l}}$  and  $\lambda$  are known.

# Finding Partial Derivatives $E_x$ , $E_y$ , $E_t$



$$E_{x_{k,l}} = \frac{1}{4} \left( E_{k+1,l,t} + E_{k+1,l,t+1} + E_{k+1,l+1,t} + E_{k+1,l+1,t+1} \right)$$
$$-\frac{1}{4} \left( E_{k,l,t} + E_{k,l,t+1} + E_{k,l+1,t} + E_{k,l+1,t+1} \right)$$

Similarly find  $E_{y_{k,l}}$  and  $E_{t_{k,l}}$ 

## Results: Rotating Ball

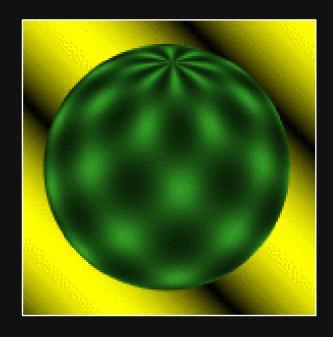
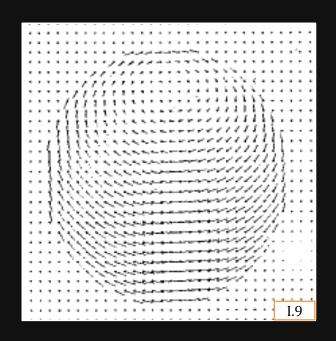


Image Sequence (2 Frames)



Optical Flow ((Himal Renults))

# Results: Rotating Camera



Image Sequence

(2 Frames)

**Optical Flow** 

(Final Result)

## Remarks: Low Texture Region (Bad)



Small gradient magnitude, can't compute flow

# Remarks: Edges (Aperture Problem)



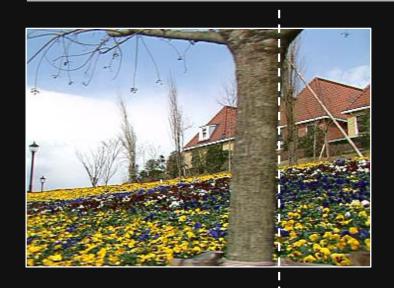
Large gradient magnitude, but constant along the edge

# Remarks: High Texture Region (Good)



Large and diverse gradient magnitudes

### What if we have large motion?





#### Taylor Series Expansion:

$$E(x + \delta x, y + \delta y, t + \delta t) =$$

$$E(x, y, t) + E_x \delta x + E_y \delta y + E_t \delta t$$

$$+O(\delta x^2,\delta y^2,\delta t^2)$$

Higher order terms cannot be ignored

#### Constraint Equation is Invalid!

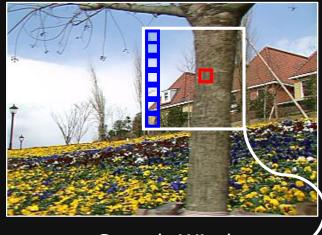
$$E_x u + E_y v + E_t \neq 0$$

#### Determine Flow using Template Matching



Template Window T

Image  $E_1$  at time t



Search Window W

Image  $E_2$  at time  $t + \delta t$ 

For each template window T in image  $E_1$ , find the corresponding match in image  $E_2$ .

## Similarity Metrics for Template Matching

Find pixel  $(k, l) \in W$  with Minimum Sum of Absolute Differences:

$$SAD(k, l) = \sum_{(i,j) \in T} |E_1(i,j) - E_2(i+k,j+l)|$$

Find pixel  $(k, l) \in W$  with Minimum Sum of Squared Differences:

$$SSD(k,l) = \sum_{(i,j)\in T} |E_1(i,j) - E_2(i+k,j+l)|^2$$

Find pixel  $(k, l) \in W$  with Minimum Normalized Cross-Correlation:

$$NCC(k,l) = \frac{\sum_{(i,j)\in T} |E_1(i,j) - E_2(i+k,j+l)|^2}{\sqrt{\sum_{(i,j)\in T} |E_1(i,j)|^2 \sum_{(i,j)\in T} |E_2(i+k,j+l)|^2}}$$

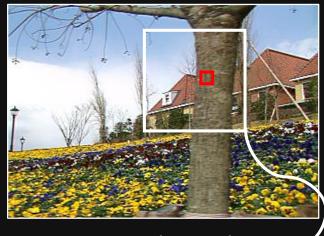
(See Image Processing Lecture 1)

#### Determine Flow using Template Matching



Template Window T

Image  $E_1$  at time t



Search Window W

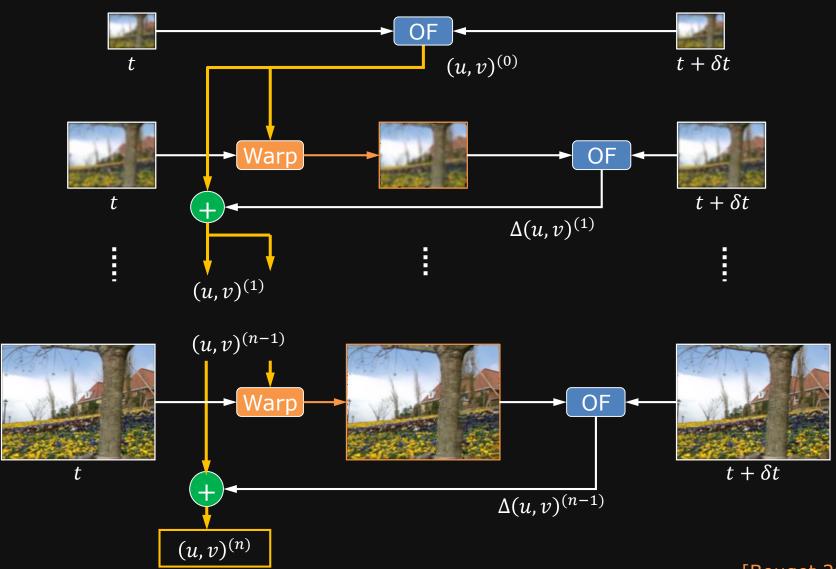
Image  $E_2$  at time  $t + \delta t$ 

Template matching is slow when search window W is large.

#### Coarse-to-fine estimation of optical flow



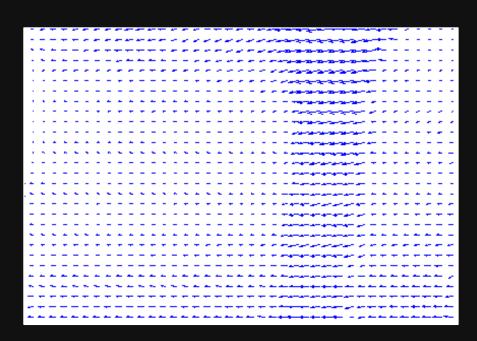
At lowest resolution, motion  $\leq 1$  pixel



# Result: Large Motion



Image Sequence



**Optical Flow** 

## Result: Optical Flow on Video



Optical flow computed on video frames

## Application: Video Retiming



Optical Flow is used to determine the intermediate frames when producing slow motion effects.

## Application: Image Stabilization



Optical Flow is used to stabilize camera shake.

### References

[Barron 2005] J. L. Barron, D. J. Fleet, and S. Beauchemin, "Performance of optical flow techniques". IJCV, 2005.

[Black 1993] M. J. Black and P. Anandan, "A framework for the robust estimation of optical flow." ICCV, 1993.

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[Horn 1981] B. K. P. Horn and B. G. Schunck, "Determining optical flow." Artificial Intelligence, 1981.

[Lucas 1981] B. D. Lucas and T. Kanade, "An iterative image registration technique with an application to stereo vision". Proceedings of Imaging understanding workshop, 1981.

## **Image Credits**

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