

# Lecture 23: Motion Vectors

ECE 417: Multimedia Signal Processing  
Mark Hasegawa-Johnson

University of Illinois

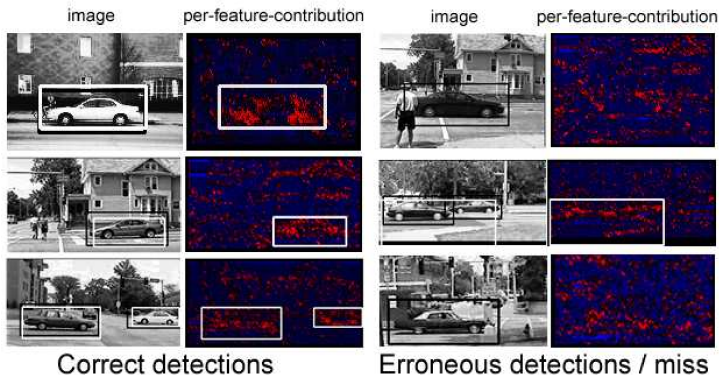
11/13/2017





# Outline

# Object Detection



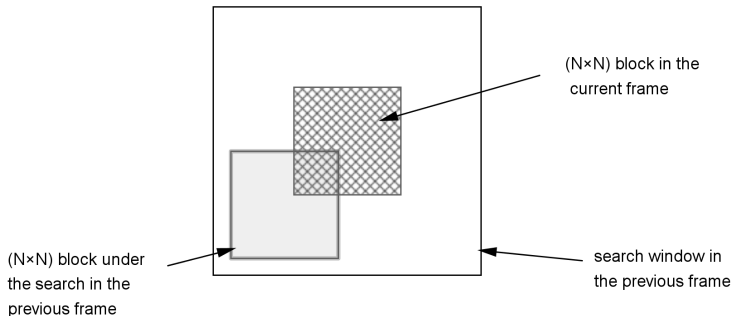
Zhuang, Zhou, Hasegawa-Johnson & Huang, "Efficient Object Localization with Gaussianized Vector Representation," IMCE 2009

# Object Detection vs. Motion Vectors

- You already know that an “object detector” looks for rectangles in the image that match some pre-defined appearance classifier.
- A “motion vector” is calculated by finding a correspondence between rectangles at time  $t$ , and rectangles at time  $t - 1$ , where  $t$  is the frame index in a video signal.

$$\vec{v} = \arg \min \|I(x, y, t) - I(x - v_1, y - v_2, t - 1)\|$$

# Motion Vectors



By German iris - Own work, CC BY-SA 4.0,  
<https://commons.wikimedia.org/w/index.php?curid=472>

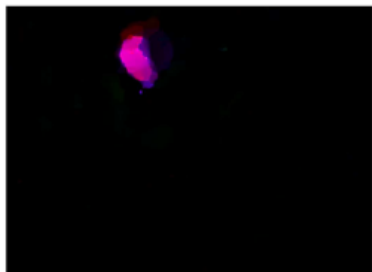
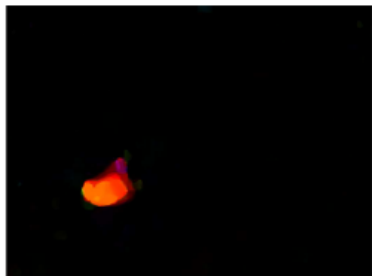
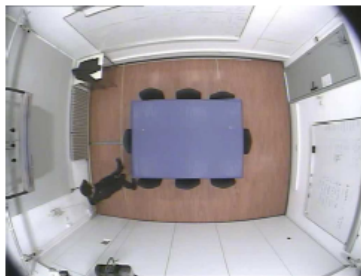
# Applications of Motion Vectors: Video Coding

- Motion vectors were originally invented for video coding.
- For example, suppose that the pixels in a video are coded with 8 bits normally,  $0 \leq I(x, y, t) \leq 255$ .
- Suppose you can find  $\vec{v}$  so that  $-8 \leq \Delta I(x, y, t) \leq 7$ , where

$$\Delta I(x, y, t) = I(x, y, t) - I(x - v_1, y - v_2, t - 1)$$

- Then you can code  $\Delta I(x, y, t)$  using just 4 bits/pixel, instead of 8 bits/pixel.

# Applications of Motion Vectors: Object Tracking



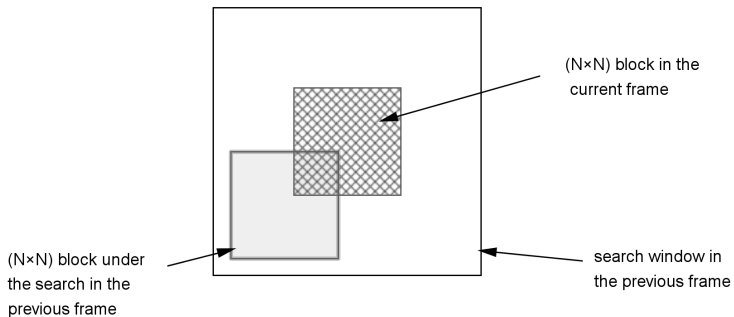


# Applications of Motion Vectors: Person Detection, Surveillance



# Outline

# The Block-Match Algorithm



# The Block-Match Algorithm

For each position,  $\vec{r}$ , in the frame at time  $t$ , we find a position  $\vec{r} - \vec{v}$  at time  $t - 1$  that best matches it. Here “best” is defined as minimum distance, e.g.,

$$\vec{v}(\vec{r}) = \arg \min \frac{1}{N^2} \sum_{\vec{m}=(1,1)}^{(N,N)} |I(\vec{r} + \vec{m}, t) - I(\vec{r} + \vec{m} - \vec{v}(\vec{r}), t - 1)|$$

or mean-squared error (MSE):

$$\vec{v}(\vec{r}) = \arg \min \frac{1}{N^2} \sum_{\vec{m}=(1,1)}^{(N,N)} |I(\vec{r} + \vec{m}, t) - I(\vec{r} + \vec{m} - \vec{v}(\vec{r}), t - 1)|^2$$

where  $\vec{r} = [r_1, r_2]$  is the location of a size  $N \times N$  block, and  $\vec{v}(\vec{r})$  is the motion vector.

# Computational Complexity

- The block-match algorithm is kind of computationally expensive.
- You have to check  $N^2$  different possible velocity vectors. . .
- . . . each of which requires  $N^2$  additions. . .
- . . . for every block in the image.
- Various sub-optimal search algorithms try to get close to finding the perfect velocity vector, without actually evaluating all  $N^2$  of the possible velocity vectors.

## Three-Step Search

- 1 Examine the 17 velocity vectors of the form

$\vec{v} \in [\{-S, 0, S\}, \{-S, 0, S\}]$ ,  
where  $S \in \{0, 1, 4\}$ . Find the best  $\vec{v}$  in this set.

- 2 Move the origin to the value of  $\vec{v}$  with best match.
- 3 Repeat this process twice more.

## Three-Step Search

	A	B	C	D	E	F	G	H	I
1	1				1				1
2									
3									
4				1	1	1			
5	1			1	0	1			1
6				1	1	1			
7									
8									
9	1				1				1
10									
11									

# Outline

# Optical Flow

The basic idea of “optical flow” is that we treat the motion vector as a function of **continuous** position, rather than **discrete** position.

$$I(x+\Delta x, y+\Delta y, t+\Delta t) = I(x, y, t) + \frac{\partial I}{\partial x} \Delta x + \frac{\partial I}{\partial y} \Delta y + \frac{\partial I}{\partial t} \Delta t + \text{H.O.T}$$

In practice, we can measure the derivatives using some kind of discrete approximations, like

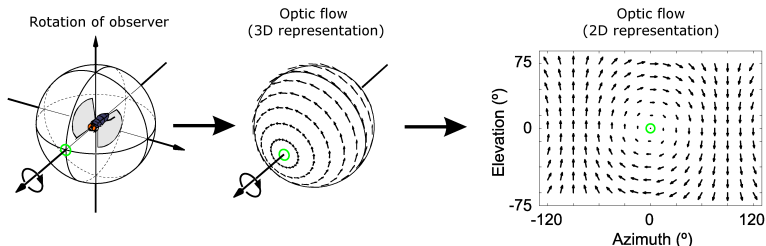
$$\frac{\partial I}{\partial x} = I(x, y, t) - I(x-1, y, t)$$

$$\frac{\partial I}{\partial y} = I(x, y, t) - I(x, y-1, t)$$

$$\frac{\partial I}{\partial t} = I(x, y, t) - I(x, y, t-1)$$



# Optical Flow



Adapted from PLoS Biology (CC licensed) article: Huston SJ, Krapp HG, 2008 Visuomotor Transformation in the Fly Gaze Stabilization System. PLoS Biol 6(7): e173.  
doi:10.1371/journal.pbio.0060173.

# Optical Flow

Suppose we require that

$$I(x+\Delta x, y+\Delta y, t+\Delta t) = I(x, y, t) + \frac{\partial I}{\partial x} \Delta x + \frac{\partial I}{\partial y} \Delta y + \frac{\partial I}{\partial t} \Delta t + \text{H.O.T}$$

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t)$$

That gives

$$0 \approx \frac{\partial I}{\partial x} \Delta x + \frac{\partial I}{\partial y} \Delta y + \frac{\partial I}{\partial t} \Delta t$$

# Optical Flow

$$\begin{aligned} 0 &= \frac{\partial I}{\partial x} \frac{\Delta x}{\Delta t} + \frac{\partial I}{\partial y} \frac{\Delta y}{\Delta t} + \frac{\partial I}{\partial t} \frac{\Delta t}{\Delta t} \\ &= \frac{\partial I}{\partial x} V_x + \frac{\partial I}{\partial y} V_y + \frac{\partial I}{\partial t} \end{aligned}$$

Re-arranging, we get **the optical flow equation**:

$$\nabla I^T \vec{v} = -b$$

where we define  $b = \frac{\partial I}{\partial t}$ , and

$$\nabla I = \left[ \frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right]^T$$

$$\mathbf{OpticalFlow} : \nabla I^T \vec{v} = -b$$

Optical flow algorithms try to minimize  $b^2$ , by making different assumptions about  $\vec{v}$ .

- Lucas-Kanade assumes that  $\vec{v}$  and  $\partial I / \partial t$  are constant within a block.
- Horn-Schunck minimizes  $\|\nabla \vec{v}\|$ , assuming that  $\partial I / \partial t = 0$ .

# Lucas-Kanade Algorithm

Suppose we have a block of  $N$  pixels, in which we can measure  $\nabla I(\vec{r}_i)$ , for  $1 \leq i \leq N$ .

- Assume that  $\vec{v}(\vec{r}_i) = \vec{v}$ , a constant.
- Assume that we can measure, at every pixel  $\vec{r}_i$ , the measurements  $\frac{\partial I(\vec{r}_i)}{\partial x}$ ,  $\frac{\partial I(\vec{r}_i)}{\partial y}$ , and  $\frac{\partial I(\vec{r}_i)}{\partial t}$ .
- Then  $\nabla I^T \vec{v} = -\frac{\partial I}{\partial t}$  gives

$$\begin{bmatrix} \frac{\partial I(\vec{r}_1)}{\partial x} & \frac{\partial I(\vec{r}_1)}{\partial y} \\ \vdots & \vdots \\ \frac{\partial I(\vec{r}_N)}{\partial x} & \frac{\partial I(\vec{r}_N)}{\partial y} \end{bmatrix} \vec{v} = - \begin{bmatrix} \frac{\partial I(\vec{r}_1)}{\partial t} \\ \vdots \\ \frac{\partial I(\vec{r}_N)}{\partial t} \end{bmatrix} + \vec{e}$$

- We can write that as

$$A\vec{v} = -\vec{b}$$

# Lucas-Kanade Algorithm

Lucas-Kanade gives us

$$A\vec{v} \approx -\vec{b}$$

To minimize the error of the approximation, we want

$$\vec{v} = \arg \min E$$

where

$$E = \|A\vec{v} + \vec{b}\|^2$$

The solution is given by the pseudo-inverse:

$$\vec{v} = -(A^T A)^{-1} A^T \vec{b}$$

# Outline

# Conclusions

- Motion vectors can be used for video coding, object tracking, and person detection.
- Motion vectors can be computed using the block-matching algorithm, but computational complexity is kind of high, because we have to search for the best possible velocity vector out of an  $N \times N$  set of possible velocity vectors.
- Optical flow computes a velocity vector at every pixel (actually, it treats the velocity vector as a continuously varying function of position)
- The optical flow equation,  $\nabla I^T \vec{v} = -\frac{\partial I}{\partial t}$ , is under-determined: both  $\vec{v}$  and  $\frac{\partial I}{\partial t}$  are unknown.
- The Lucas-Kanade algorithm assumes that both unknowns are constant over a local block, and solves using the pseudo-inverse.