## CS9840
## Learning and Computer Vision
## Prof. Olga Veksler

# Lecture 2

Linear Machines, Optical Flow

Some Slides are from Cornelia, Fermüller,
Mubarak Shah,
Gary Bradski,
Sebastian Thrun

## Last Time: Supervised Learning

- Training samples (or examples) $X^1, X^2, \dots X^n$
- Each example is typically multi-dimensional
  - $X^i_1, X^i_2, \dots, X^i_d$ are typically called *features*, $X^i$ is sometimes called a *feature vector*
  - **How many features and which features do we take?**
- Know desired output for each example (labeled samples) $Y^1, Y^2, \dots Y^n$
  - This learning is supervised ("teacher" gives desired outputs).
  - $Y^i$ are often one-dimensional, but can be multidimensional

## Outline

- Linear Machines
- Start preparation for the first paper
  - *"Recognizing Action at a Distance" by A. Efros, A.Berg, G. Mori, Jitendra Malik*
  - there should be a link to PDF file on our web site
- Next time:
  - Discuss the paper and watch video
  - Prepare for the second paper

## Last Time: Supervised Learning

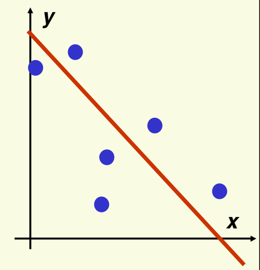
- Wish to design a *machine* f(X,W) s.t. f(X,W) = true output value at X
  - In classification want f(X,W) = label of X
  - **How do we choose f?**
    - when we choose a particular f, we are making implicit assumptions about our problem
  - W is typically multidimensional vector of weights (also called *parameters*) which enable the machine to "learn"
    - $W = [w_1, w_2, \dots w_k]$

## Training and Testing

- There are 2 phases, training and testing
  - Divide all labeled samples $X^1, X^2, \ldots X^n$ into 2 sets, *training* set and *testing* set
  - Training phase is for "teaching" our machine (finding optimal weights W)
  - Testing phase is for evaluating how well our machine works on unseen examples
- Training phase
  - Find the weights W s.t. $f(X^i,W) = Y^i$ "as much as possible" for the *training* samples $X^i$
  - "as much as possible" needs to be defined
  - Training can be quite complex and time-consuming

## Linear Machine, Continuous Y

- $f(X,W) = w_0+\Sigma_{i=1,2,\ldots d}\, w_i x_i$
  - $w_0$ is called bias
- In vector form, if we let $X = (1,x_1,x_2,\ldots,x_d)$, then $f(X,W) = W^T X$
  - notice abuse of notation, I made $X=[1\ X]$
- This is standard linear regression (line fitting)
  - assume $L(X^i,Y^i,W) = \|\, f(X^i,W) - Y^i \,\|^2$
  - optimal W can be found by solving linear system of equations $W^* = [\Sigma X^i (X^i)^T]^{-1}\, \Sigma Y^i X^i$

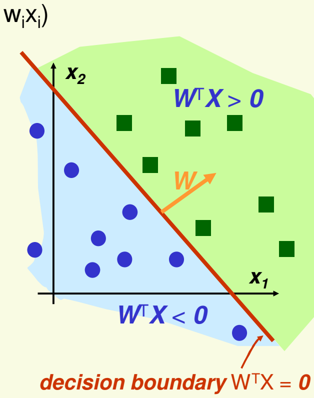



## Loss Function

- How do we quantify what it means for the machine f(X,W) do well in the training and testing phases?
- f(X,W) has to be "close" to the true output on X
- Define Loss (or Error) function L
  - This is up to the designer (that is you)
- Typically first define per-sample loss $L(X^i,Y^i,W)$
  - Some examples:
    - for classification, $L(X^i,Y^i,W) = \mathbf{I}[f(X^i,W) \neq Y^i]$, where $\mathbf{I}[\text{true}] = 1$, $\mathbf{I}[\text{false}] = 0$
      - we just care if the sample has been classified correctly
    - For continuous Y, $L(X^i,Y^i,W) = \|\, f(X^i,W) - Y^i \,\|^2$,
      - how far is the estimated output from the correct one?
- Then loss function $L = \Sigma_i L(X^i,Y^i,W)$
  - Number of missclassified example for classification
  - Sum of distances from the estimated output to the correct output

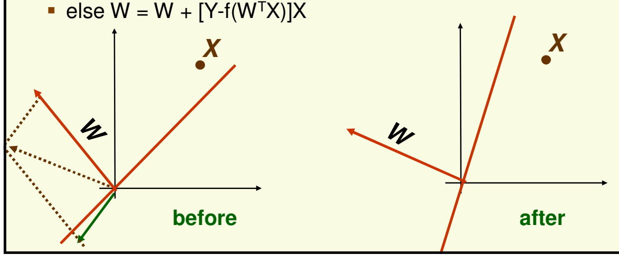
## Linear Machine: binary Y

- $f(X,W) = \text{sign}(w_0+\Sigma_{i=1,2,\ldots d}\, w_i x_i)$
  - sign(positive) = 1, sign(negative) = -1
  - $w_0$ is called bias
- In vector form, if we let $X = (1,x_1,x_2,\ldots,x_d)$ then $f(X,W) = \text{sign}(W^T X)$



## Perceptron Learning Procedure (Rosenblatt 1957)

- $f(X,W) = \text{sign}(w_0+\Sigma_{i=1,2,\dots d}\, w_i x_i)$
- Let $L(X^i,Y^i,W) = \mathbf{I}[f(X^i,W) \neq Y^i]$. How do we learn W?
- A solution:
- Iterate over all training samples
  - if f(X,W)=Y (correct label), do nothing
  - else $W = W + [Y-f(W^TX)]X$




## Optimization

- Need to minimize a function of many variables

$$J(x) = J(x_1,\dots,x_d)$$

- We know how to minimize $J(x)$
  - Take partial derivatives and set them to zero

$$\begin{bmatrix} \frac{\partial}{\partial x_1} J(x) \\ \vdots \\ \frac{\partial}{\partial x_d} J(x) \end{bmatrix} = \underbrace{\nabla J(x)}_{\text{gradient}} = 0$$

- However solving analytically is not always easy
  - Would you like to solve this system of nonlinear equations?

$$\begin{cases} \sin(x_1^2 + x_2^3) + e^{x_4^2} = 0 \\ \cos(x_1^2 + x_2^3) + \log(x_5^3)^{x_4^2} = 0 \end{cases}$$

  - Sometimes it is not even possible to write down an analytical expression for the derivative, we will see an example later today

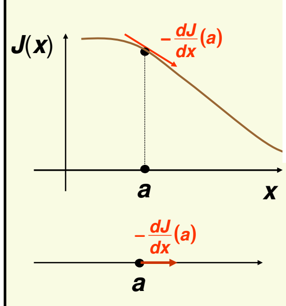
## Perceptron Learning Procedure (Rosenblatt 1957)

- Amazing fact: If the samples are linearly separable, the perceptron learning procedure will converge to a solution (separating hyperplane) in a finite amount of time
- Bad news: If the samples are not linearly separable, the perceptron procedure will not terminate, it will go on looking for a solution which does not exist!
- For most interesting problems the samples are not linearly separable
- Is there a way to learn W in non-separable case?
  - Remember, it's ok to have training error, so we don't have to have "perfect" classification

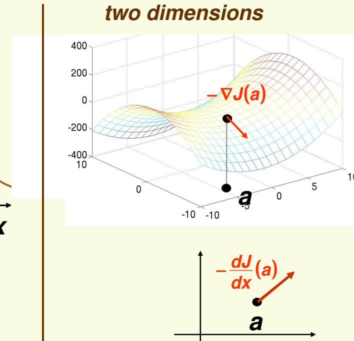
## Optimization: Gradient Descent

- Gradient $\nabla J(x)$ points in direction of steepest increase of $J(x)$, and $-\nabla J(x)$ in direction of steepest decrease

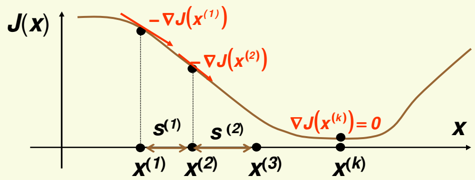
*one dimension*




*two dimensions*



## Optimization: Gradient Descent




***Gradient Descent*** for minimizing any function $J(x)$

set $k = 1$ and $x^{(1)}$ to some initial guess for the weight vector

while $\eta^{(k)} \left| \nabla J(x^{(k)}) \right| > \varepsilon$

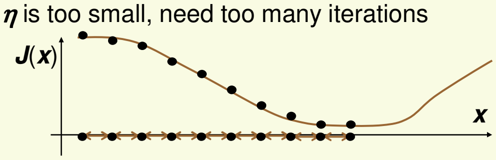
*choose learning rate* $\eta^{(k)}$

$x^{(k+1)} = x^{(k)} - \eta^{(k)} \nabla J(x)$ (***update rule***)

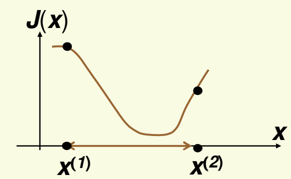
$k = k + 1$

## Optimization: Gradient Descent

- Main issue: how to set parameter $\eta$ (***learning rate***)
- If $\eta$ is too small, need too many iterations

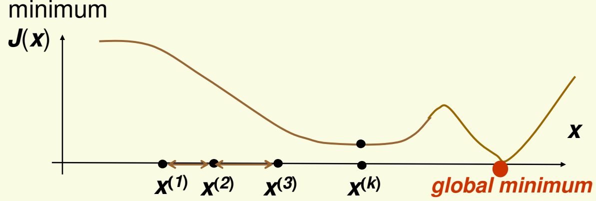



- If $\eta$ is too large may overshoot the minimum and possibly never find it (if we keep overshooting)




## Optimization: Gradient Descent

- Gradient descent is guaranteed to find only a local minimum



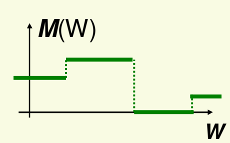

- Nevertheless gradient descent is very popular because it is simple and applicable to any differentiable function

## "Optimal" W with Gradient Descent

- $f(X,W) = \text{sign}(w_0 + \Sigma_{i=1,2,\dots d}\, w_i x_i)$
- If we let $L(X^i,Y^i,W) = \mathbf{I}[f(X^i,W) \neq Y^i]$, then $L(W)$ is the number of missclassified examples
- Let $M$ be the set of examples misclassified by $W$

$$M(W) = \{\textit{sample } X^i \textit{ s.t. } W^T X^i \neq Y^i\}$$

- Then $L(W) = |M(W)|$, the size of $M(W)$
- $L(W)$ is piecewise constant, gradient descent is useless

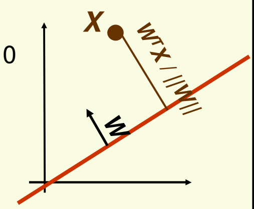


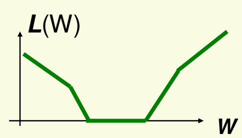
## "Optimal" W with Gradient Descent

- Better choice:

$$L(W) = \sum_{X^i \in M} \left(-W^T X^i\right) Y^i$$

- If $X^i$ is misclassified, $(W^T X^i) Y^i \leq 0$
- Thus $L(W, X^i, Y^i) \geq 0$
- $L(W, X^i, Y^i)$ is proportional to the distance of misclassified example to the decision boundary
- $L(W) = \Sigma L(W, X^i, Y^i)$ is piecewise linear and thus suitable for gradient decent




## Single Sample Rule

- Thus *gradient decent single sample rule* for $L(W)$ is:

$$W^{(k+1)} = W^{(k)} + \eta^{(k)}(XY)$$

  - apply for any sample X misclassified by $W^{(k)}$
  - must have a consistent way of visiting samples

## Batch Rule

$$L(W, X^i, Y^i) = \sum_{X \in M} \left(-W^T X\right) Y$$

- Gradient of $L$ is $\nabla L(W) = \sum_{X \in M} (-X) Y$
  - $M$ are samples misclassified by W
  - It is not possible to solve $\nabla L(W) = 0$ analytically
- Update rule for gradient descent: $x^{(k+1)} = x^{(k)} - \eta^{(k)} \nabla J(x)$
- Thus *gradient decent batch update rule* for $L(W)$ is:

$$W^{(k+1)} = W^{(k)} + \eta^{(k)} \sum_{Y \in M} XY$$

- It is called batch rule because it is based on all misclassified examples

## Convergence

- If classes are linearly separable, and $\eta^{(k)}$ is fixed to a constant, i.e. $\eta^{(1)} = \eta^{(2)} = \ldots = \eta^{(k)} = c$ (*fixed learning rate*)
  - *both single sample and batch rules converge to a correct solution* (could be any $W$ in the solution space)
- If classes are not linearly separable:
  - Single sample algorithm does not stop, it keeps looking for solution which does not exist
  - However by choosing appropriate learning rate, heuristically stop algorithm at hopefully good stopping point

$$\eta^{(k)} \to 0 \text{ as } k \to \infty$$

  - for example, $\eta^{(k)} = \dfrac{\eta^{(1)}}{k}$
  - for this learning rate convergence in the linearly separable case can also be proven

## Learning by Gradient Descent

- Suppose we suspect that the machine has to have functional form f(X,W), not necessarily linear
- Pick differentiable per-sample loss function $L(X^i,Y^i,W)$
- We need to find W that minimizes $L = \Sigma_i L(X^i,Y^i,W)$
- Use gradient-based minimization:
  - Batch rule: $W = W - \eta \nabla L(W)$
  - Or single sample rule: $W = W - \eta \nabla L(X^i,Y^i,W)$

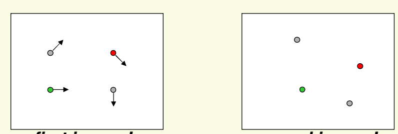
## Background Preparation for Paper

- Paper: *"Recognizing Action at a Distance" by A. Efros, A.Berg, G. Mori, Jitendra Malik*
  - Optical Flow Field (related to motion field)
  - Correlation

## Important Questions

- How do we choose the feature vector X?
- How do we split labeled samples into training/testing sets?
- How do we choose the machine f(X,W)?
- How do we choose the loss function $L(X^i,Y^i,W)$?
- How do we find the optimal weights W?

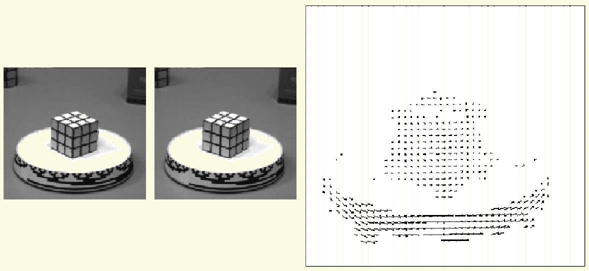
## Optical flow



***first image $I_1$*** ***second image $I_2$***

- How to estimate pixel motion from image $I_1$ to image $I_2$?
  - Solve pixel correspondence problem
    - given a pixel in $I_1$, look for **nearby** pixels of the **same** color in $I_2$
- Key assumptions
  - **color constancy:** a point in $I_1$ looks the same in $I_2$
    - For grayscale images, this is **brightness constancy**
  - **small motion**: points do not move very far
- This is called the **optical flow** problem

## Optical Flow Field



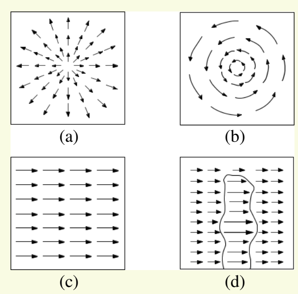
## Motion Field (MF)

- The MF assigns a velocity vector to each pixel in the image
- These velocities are INDUCED by the RELATIVE MOTION between the camera and the 3D scene
- The MF is the *projection* of the 3D velocities on the image plane

## Optical Flow and Motion Field

- Optical flow field is the apparent motion of brightness patterns between 2 (or several) frames in an image sequence
- Why does brightness change between frames?
- Assuming that illumination does not change:
  - changes are due to the RELATIVE MOTION between the scene and the camera
  - There are 3 possibilities:
    - Camera still, moving scene
    - Moving camera, still scene
    - Moving camera, moving scene

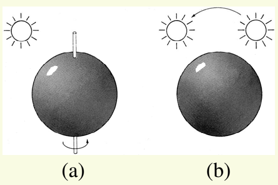
## Examples of Motion Fields




(a) Translation perpendicular to a surface. (b) Rotation about axis perpendicular to image plane. (c) Translation parallel to a surface at a constant distance. (d) Translation parallel to an obstacle in front of a more distant background.

## Optical Flow vs. Motion Field

- Recall that Optical Flow is the apparent motion of brightness patterns
- We equate Optical Flow Field with Motion Field
- Frequently works, but now always:




(a) A smooth sphere is rotating under constant illumination. Thus the optical flow field is zero, but the motion field is not

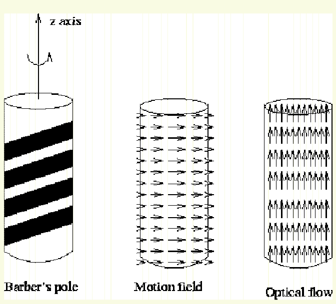
(b) A fixed sphere is illuminated by a moving source—the shading of the image changes. Thus the motion field is zero, but the optical flow field is not

## Computing Optical Flow: Brightness Constancy Equation

- Let ***P*** be a moving point in 3D:
  - At time ***t***, ***P*** has coordinates (***X***(***t***),***Y***(***t***),***Z***(***t***))
  - Let ***p***=(***x***(***t***),***y***(***t***)) be the coordinates of its image at time ***t***
  - Let ***E***(***x***(***t***),***y***(***t***),***t***) be the brightness at ***p*** at time ***t***.
- Brightness Constancy Assumption:
  - As ***P*** moves over time, ***E***(***x***(***t***),***y***(***t***),***t***) remains constant

## Optical Flow vs. Motion Field

- Often (but not always) optical flow corresponds to the true motion of the scene




## Computing Optical Flow: Brightness Constancy Equation

$$E(x(t), y(t), t) = Constant$$

Taking derivative wrt time:

$$\frac{dE(x(t), y(t), t)}{dt} = 0$$

$$\frac{\partial E}{\partial x}\frac{dx}{dt} + \frac{\partial E}{\partial y}\frac{dy}{dt} + \frac{\partial E}{\partial t} = 0$$

## Computing Optical Flow: Brightness Constancy Equation

***1 equation with 2 unknowns***

$$\frac{\partial E}{\partial x}\frac{dx}{dt} + \frac{\partial E}{\partial y}\frac{dy}{dt} + \frac{\partial E}{\partial t} = 0$$

Let

$$\nabla E = \begin{bmatrix} \frac{\partial E}{\partial x} \\ \frac{\partial E}{\partial y} \end{bmatrix}$$ (Frame spatial gradient)

$$v = \begin{bmatrix} \frac{dx}{dt} \\ \frac{dy}{dt} \end{bmatrix}$$ (optical flow)

and

$$E_t = \frac{\partial E}{\partial t}$$ (derivative across frames)

## Video Sequence

*

* Picture from Khurram Hassan-Shafique CAP5415 Computer Vision 2003

## Computing Optical Flow: Brightness Constancy Equation

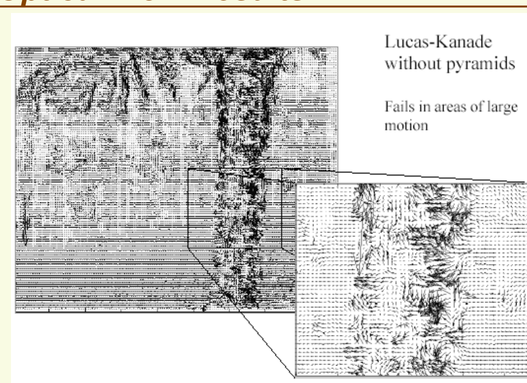
- How to get more equations for a pixel?
  - Basic idea: impose additional constraints
    - most common is to assume that the flow field is smooth locally
    - one method: pretend the pixel's neighbors have the same (u,v)
      - If we use a 5x5 window, that gives us 25 equations per pixel!

$$E_t(p_i) + \nabla E(p_i) \cdot [u \quad v] = 0$$

$$\begin{bmatrix} E_x(p_1) & E_y(p_1) \\ E_x(p_2) & E_y(p_2) \\ \vdots & \vdots \\ E_x(p_{25}) & E_y(p_{25}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = -\begin{bmatrix} E_t(p_1) \\ E_t(p_2) \\ \vdots \\ E_t(p_{25}) \end{bmatrix}$$

matrix ***E*** 25x2    vector ***d*** 2x1    vector ***b*** 25x1

## Optical Flow Results

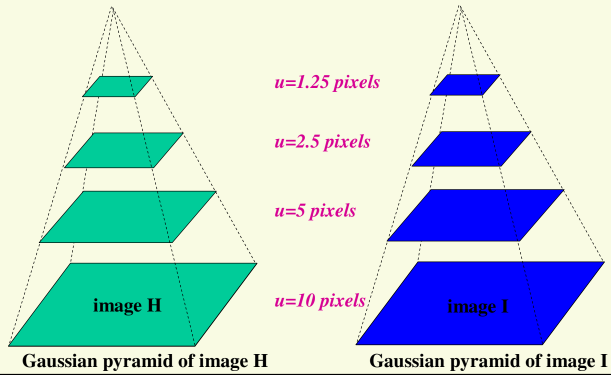



* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

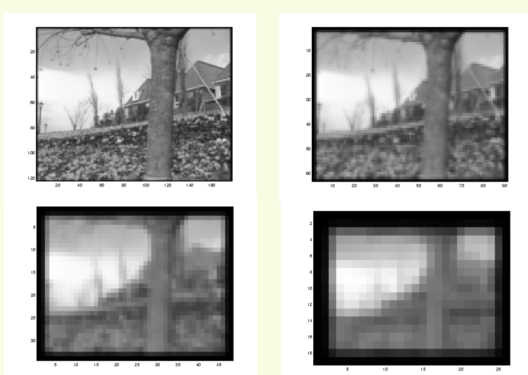
## Revisiting the small motion assumption

- Is this motion small enough?
  - Probably not—it's much larger than one pixel ($2^{nd}$ order terms dominate)
  - How might we solve this problem?

## Coarse-to-fine optical flow estimation



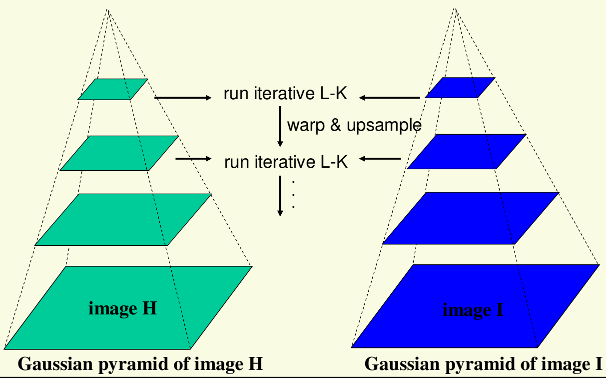

## Reduce the resolution!



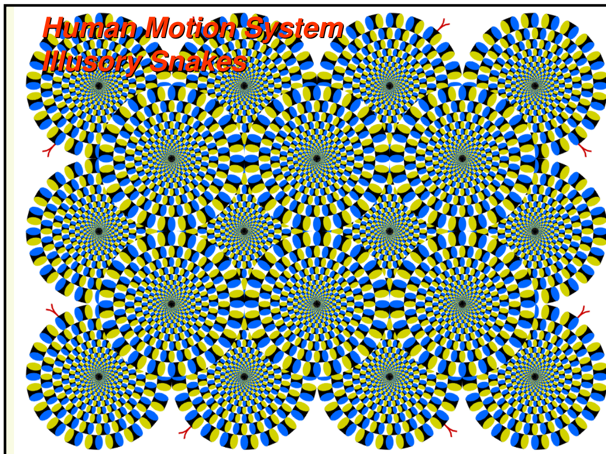
## Iterative Refinement

- Iterative Lukas-Kanade Algorithm
  1. Estimate velocity at each pixel by solving Lucas-Kanade equations
  2. Warp H towards I using the estimated flow field
     - *use image warping techniques*
  3. Repeat until convergence

## Coarse-to-fine optical flow estimation

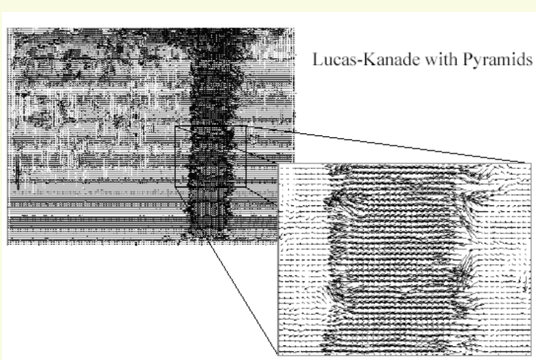



## Human Motion System
## Illusory Snakes



from Gary Bradski and Sebastian Thrun

## Optical Flow Results




* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

## Other Concepts to Review

- Convolution is the operation of applying a “kernel” to each pixel of an image

*image*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $I_{11}$ | $I_{12}$ | $I_{13}$ | $I_{14}$ | $I_{15}$ | $I_{16}$ | $I_{17}$ | $I_{18}$ | $I_{19}$ |
| $I_{21}$ | $I_{22}$ | $I_{23}$ | $I_{24}$ | $I_{25}$ | $I_{26}$ | $I_{27}$ | $I_{28}$ | $I_{29}$ |
| $I_{31}$ | $I_{32}$ | $I_{33}$ | $I_{34}$ | $I_{35}$ | $I_{36}$ | $I_{37}$ | $I_{38}$ | $I_{39}$ |
| $I_{41}$ | $I_{42}$ | $I_{43}$ | $I_{44}$ | $I_{45}$ | $I_{46}$ | $I_{47}$ | $I_{48}$ | $I_{49}$ |
| $I_{51}$ | $I_{52}$ | $I_{53}$ | $I_{54}$ | $I_{55}$ | $I_{56}$ | $I_{57}$ | $I_{58}$ | $I_{59}$ |
| $I_{61}$ | $I_{62}$ | $I_{63}$ | $I_{64}$ | $I_{65}$ | $I_{66}$ | $I_{67}$ | $I_{68}$ | $I_{69}$ |

*kernel*

| | | |
|---|---|---|
| $K_{11}$ | $K_{12}$ | $K_{13}$ |
| $K_{21}$ | $K_{22}$ | $K_{23}$ |

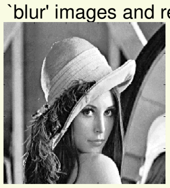
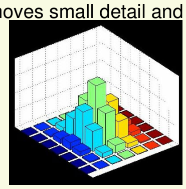
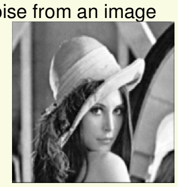
- Result of convolution has the same dimension as the image
- For example:

$$O_{57} = I_{57}K_{11} + I_{58}K_{12} + I_{59}K_{13} + I_{67}K_{21} + I_{68}K_{22} + I_{69}K_{23}$$

- Convolution is frequently denoted by *, for example I*K

## Other Concepts to Review

- Gaussian smoothing (blurring): convolution operator that is used to `blur' images and removes small detail and noise from an image

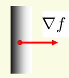
 $*$  $=$ 

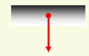
$\frac{1}{273}$

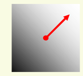
| | | | | |
|---|---|---|---|---|
| 1 | 4 | 7 | 4 | 1 |
| 4 | 16 | 26 | 16 | 4 |
| 7 | 26 | 41 | 26 | 7 |
| 4 | 16 | 26 | 16 | 4 |
| 1 | 4 | 7 | 4 | 1 |

## Other Concepts to Review

- Image gradient: points in the direction of the most rapid increase in intensity of image ***f***

 $\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$

 $\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$

 $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

- Sobel operator to compute gradient:

$\frac{1}{8}$

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -2 | 0 | 2 |
| -1 | 0 | 1 |

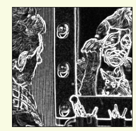
$\frac{\partial f}{\partial x}$

$\frac{1}{8}$

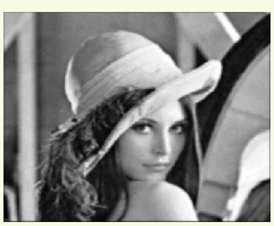
| | | |
|---|---|---|
| 1 | 2 | 1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

$\frac{\partial f}{\partial y}$

- Results:

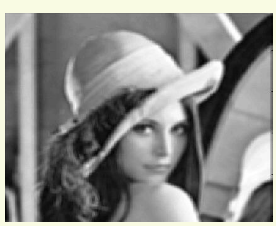
## Gaussian vs. Smoothing



Gaussian Smoothing

$\frac{1}{273}$

| | | | | |
|---|---|---|---|---|
| 1 | 4 | 7 | 4 | 1 |
| 4 | 16 | 26 | 16 | 4 |
| 7 | 26 | 41 | 26 | 7 |
| 4 | 16 | 26 | 16 | 4 |
| 1 | 4 | 7 | 4 | 1 |



Smoothing by Averaging

$\frac{1}{25}$

| | | | | |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 |

## Other Concepts to Review

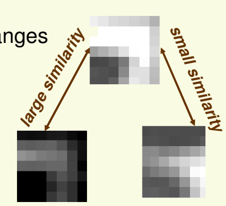
- Cross-correlation

$$c(f,g) = \sum_{i=1}^{d} f(i)g(i)$$

  - measures similarity between images (or image regions) f and g
  - works OK if there is no change in intensity

- Normalized cross correlation, more popular in image processing
  - Insensitive to linear intensity changes between image patches f and g

$$NCC(f,g) = \frac{\sum_{i=1}^{d} (f(i)-\bar{f})(g(i)-\bar{g})}{\left[\sum_{i=1}^{d} (f(i)-\bar{f})^2 \sum_{k=1}^{d} {}^2(g(i)-\bar{g})\right]^{1/2}}$$



## *Next Time*

- Paper: *"Recognizing Action at a Distance" by A. Efros, A.Berg, G. Mori, Jitendra Malik*
- When reading the paper, think about following:
  - What is the problem paper tries to solve
  - What makes this problem difficult?
  - What is the method used in the paper to solve the problem
  - What is the contribution of the paper (what new does it do)?
  - Do the experimental results look "good" to you?