Fall 2006
CS840a
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) $X^1,X^2,\ldots X^n$
- Each example is typically multi-dimensional
  - $X^i_1, X^i_2,\ldots, X^i_d$ 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) $Y^1,Y^2,\ldots Y^n$
  - 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

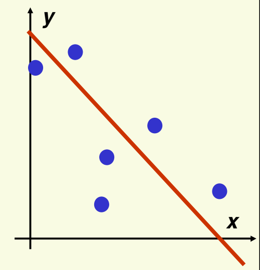
- Wish to design a *machine* f(X,W) s.t. f(X,W) = true output value at X
  - In classification want f(X,W) = label of X
  - **How do we choose f?**
    - when we choose a particular f, we are making implicit assumptions about our problem
  - W is typically multidimensional vector of weights (also called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

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 $W^* = [\Sigma X^i (X^i)^T]^{-1} \Sigma Y^i X^i$

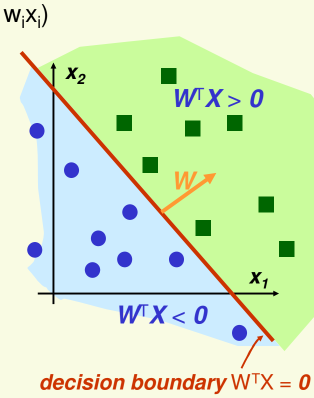


Loss Function

- 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

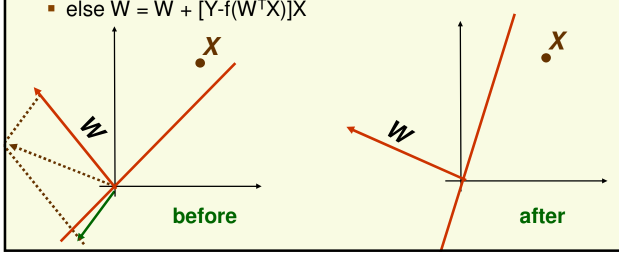
Linear Machine: binary Y

- $f(X,W) = \text{sign}(w_0+\Sigma_{i=1,2,\ldots d}\, w_i x_i)$
  - 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)

- $f(X,W) = \text{sign}(w_0+\Sigma_{i=1,2,...d}\ w_i x_i)$
- 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 $W = W + [Y\text{-}f(W^TX)]X$



Optimization

- Need to minimize a function of many variables
$$J(x) = J(x_1,\ldots,x_d)$$
- 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

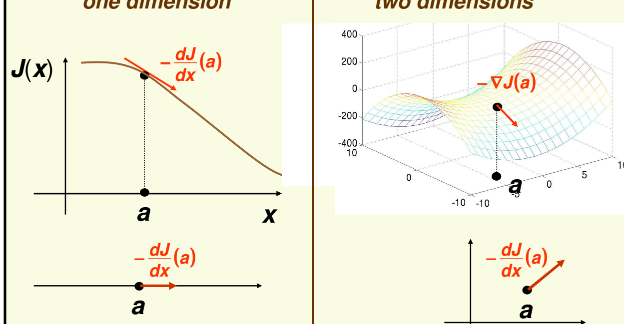
Perceptron Learning Procedure (Rosenblatt 1957)

- 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

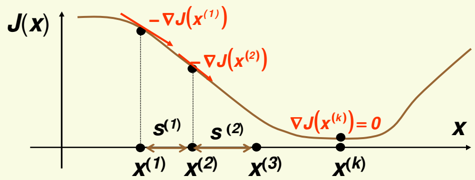
Optimization: Gradient Descent

- 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 $\boldsymbol{J}(\boldsymbol{x})$

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

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

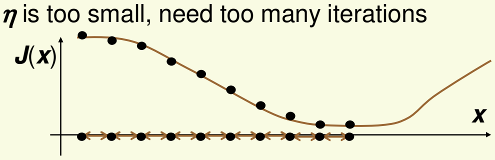
choose ***learning rate*** $\eta^{(k)}$

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

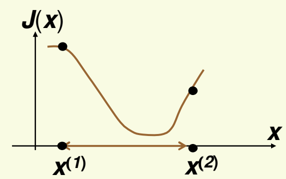
$k = k + 1$

Optimization: Gradient Descent

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

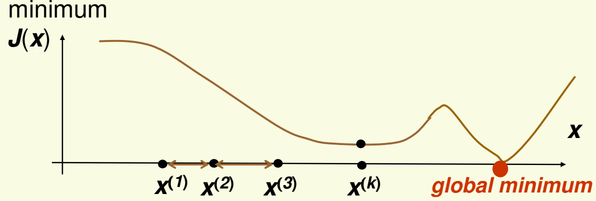


- If η is too large may overshoot the minimum and possibly never find it (if we keep overshooting)



Optimization: Gradient Descent

- Gradient descent is guaranteed to find only a local minimum



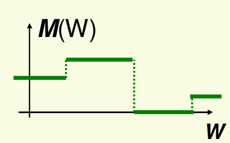
- Nevertheless gradient descent is very popular because it is simple and applicable to any differentiable function

"Optimal" W with Gradient Descent

- $f(X,W) = \text{sign}(w_0+\Sigma_{i=1,2,\ldots d}\, w_i x_i)$
- 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 $\boldsymbol{M}$ be the set of examples misclassified by $\boldsymbol{W}$

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

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

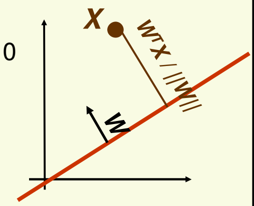


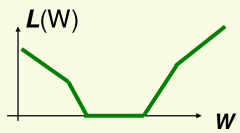
"Optimal" W with Gradient Descent

- Better choice:

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

- If X^i is misclassified, $(W^T X^i)Y^i \le 0$
- Thus $L(W,X^i,Y^i) \ge 0$
- $L(W,X^i,Y^i)$ 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: $W = W - \eta \nabla L(X^i,Y^i,W)$

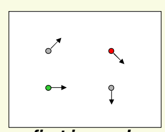
Background Preparation for Paper

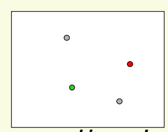
- Paper: *"Recognizing Action at a Distance" by A. Efros, A.Berg, G. Mori, Jitendra Malik*
  - Optical Flow Field (related to motion field)
  - Correlation

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?

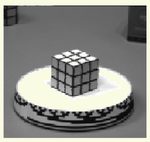
Optical flow

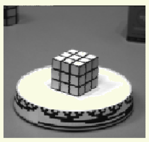

first image I_1

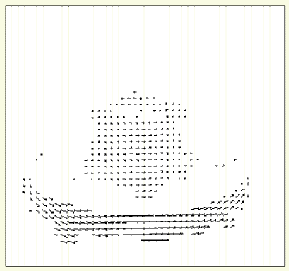

second image I_2

- 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







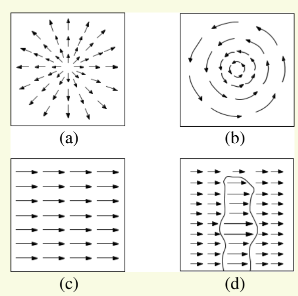
Motion Field (MF)

- 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

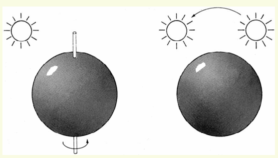
Examples of Motion Fields



(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) (b)

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

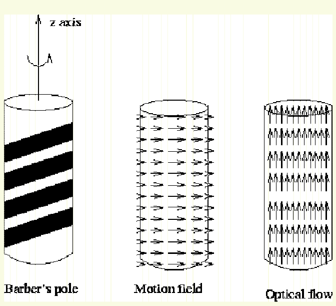
(b) A fixed sphere is illuminated by a moving source—the shading of the image changes. Thus the motion field is zero, but the optical flow field is not

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

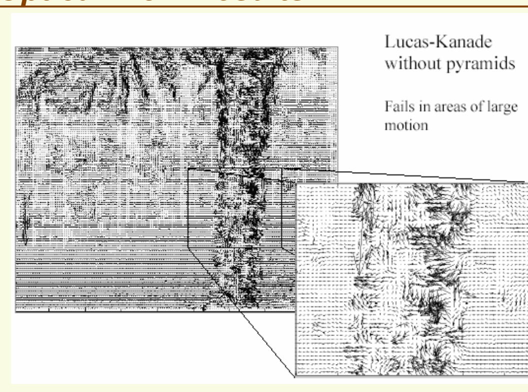
- How to get more equations for a pixel?
  - Basic idea: impose additional constraints
    - most common is to assume that the flow field is smooth locally
    - one method: pretend the pixel's neighbors have the same (u,v)
      - If we use a 5x5 window, that gives us 25 equations per pixel!

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

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

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

Optical Flow Results

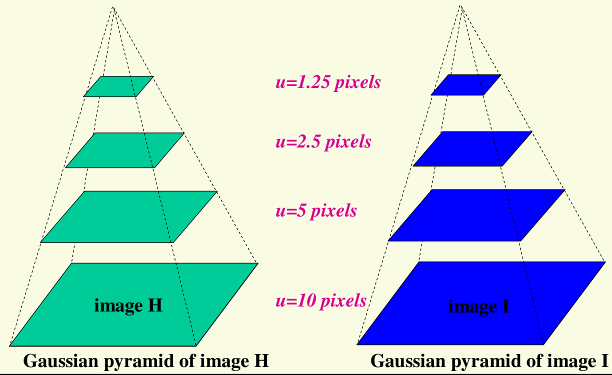


* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

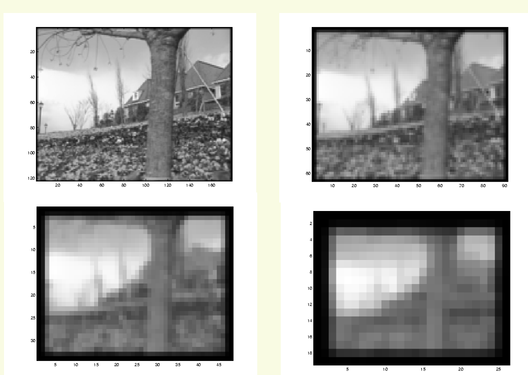
Revisiting the small motion assumption

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

Coarse-to-fine optical flow estimation



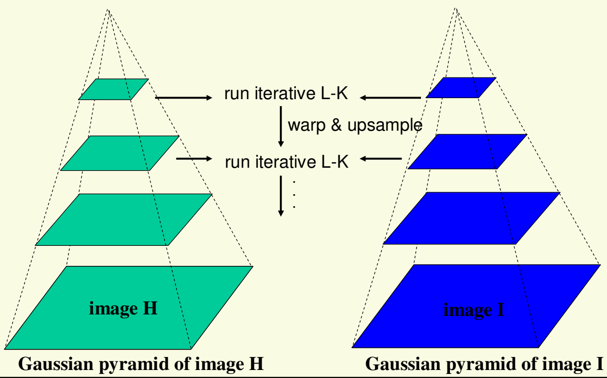
Reduce the resolution!



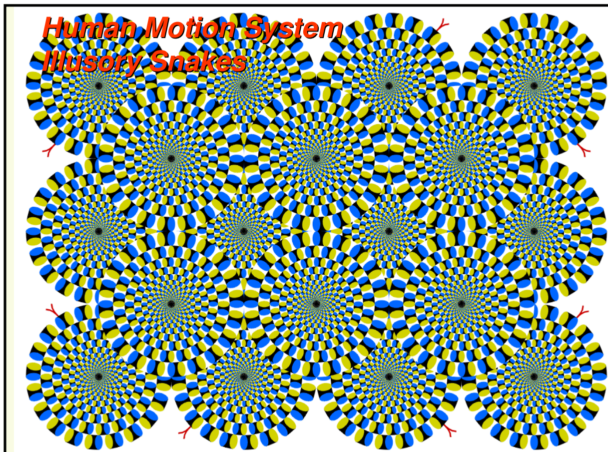
Iterative Refinement

- 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

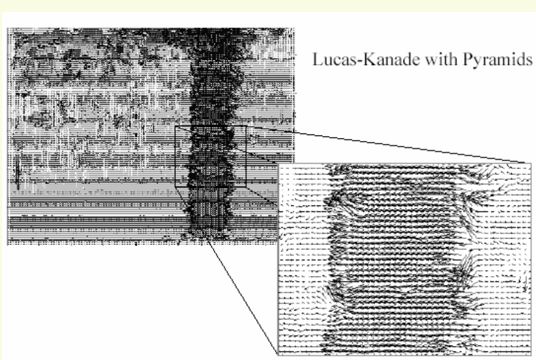


Human Motion System
Illusory Snakes



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}

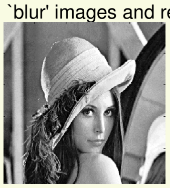
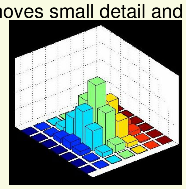
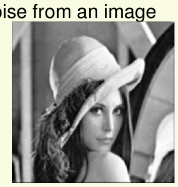
- Result of convolution has the same dimension as the image
- For example:

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

- 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

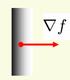
 $*$  $=$ 

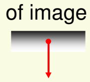
$\frac{1}{273}$

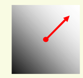
1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1

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

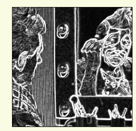
$\frac{\partial f}{\partial x}$

$\frac{1}{8}$

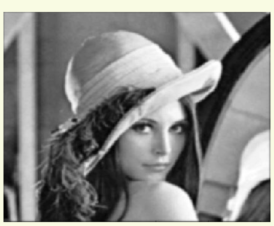
1	2	1
0	0	0
-1	-2	-1

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

- Results:

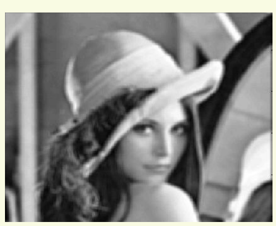
Gaussian vs. Smoothing



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

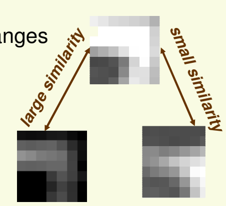
- Cross-correlation

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

  - 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

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



Next Time

- Paper:*"Recognizing Action at a Distance" by A. Efros, A.Berg, G. Mori, Jitendra Malik*
- When reading the paper, think about following:
  - Your discussion should have the following:
    - very short description of the problem paper tries to solve
    - What makes this problem difficult?
    - Short description of 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?