

# EEE-6512: Image Processing and Computer Vision

November 1, 2017

Lecture #8: Edges and Features

Damon L. Woodard, Ph.D.

Dept. of Electrical and Computer  
Engineering

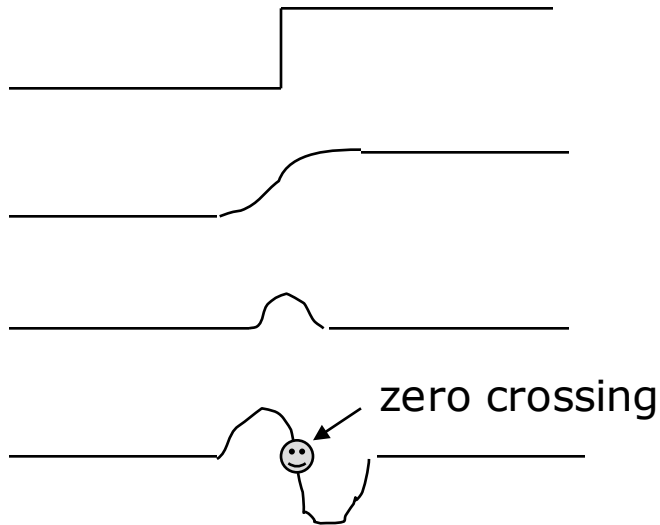
[dwoodard@ece.ufl.edu](mailto:dwoodard@ece.ufl.edu)

# **Other Edge Detectors**

(2<sup>nd</sup> Order Derivative Filters)

# Zero Crossing Operators

**Motivation:** The zero crossings of the second derivative of the image function are more precise than the peaks of the first derivative.



step edge  
smoothed

1st derivative

2nd derivative

# How do we estimate the Second Derivative?

- Laplacian Filter:  $\nabla^2 f = \partial^2 f / \partial x^2 + \partial^2 f / \partial y^2$

0	1	0
1	-4	1
0	1	0

- Standard mask implementation
- The Laplacian mask estimates the 2D second derivative.

# Marr/Hildreth Operator

- First smooth the image via a Gaussian convolution.
- Apply a Laplacian filter (estimate 2nd derivative).
- Find zero crossings of the Laplacian of the Gaussian.

This can be done at multiple resolutions.

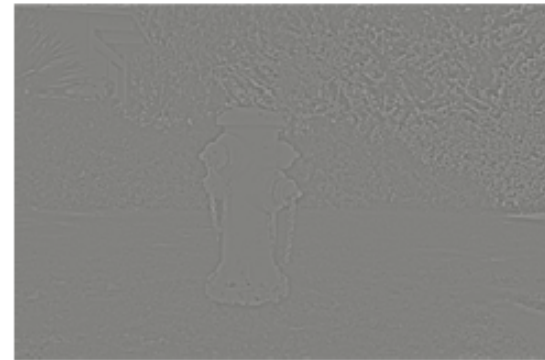
The primary drawback of the LoG is that it is isotropic, meaning that it smooths *across* as well as *along* edges, as opposed to the gradient vector.

# Marr-Hildreth Operator (cont'd)

**Figure 7.12** An image, with the result of applying the Laplacian of Gaussian (LoG) and the sign of the Laplacian of Gaussian (sLoG). The zero crossings of the LoG are an approach to edge detection that is not widely used due to the drawback of isotropic smoothing.



Image



LoG



Zero crossings

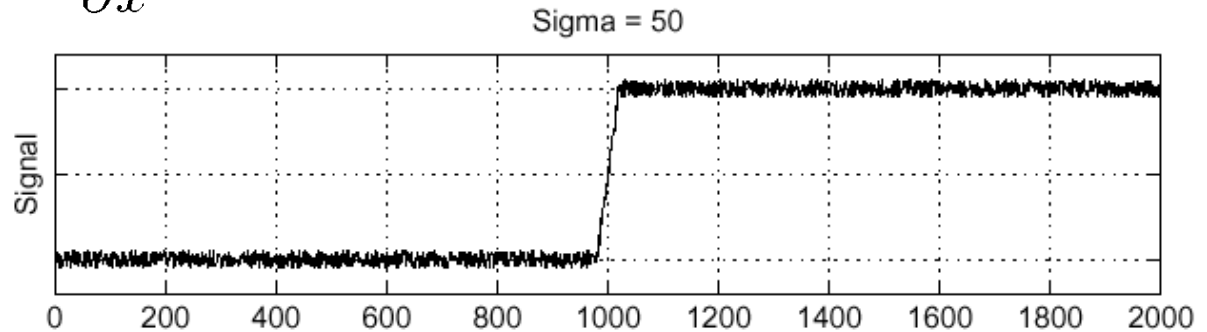


Sign of the LoG (sLoG)

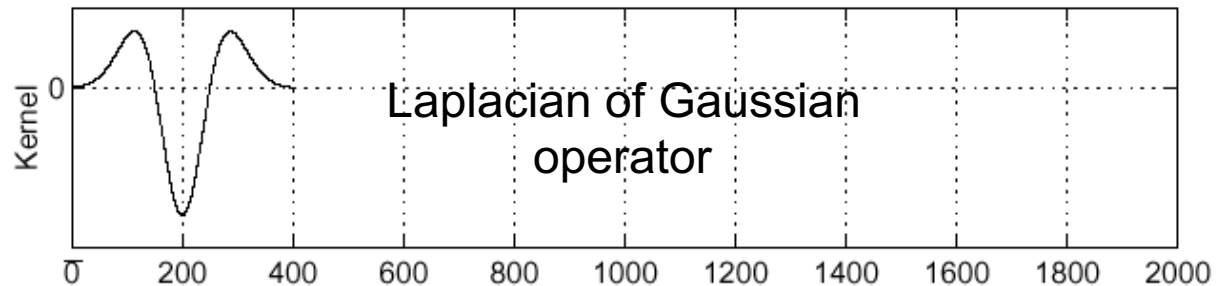
# Laplacian of Gaussian

- Consider  $\frac{\partial^2}{\partial x^2}(h \star f)$

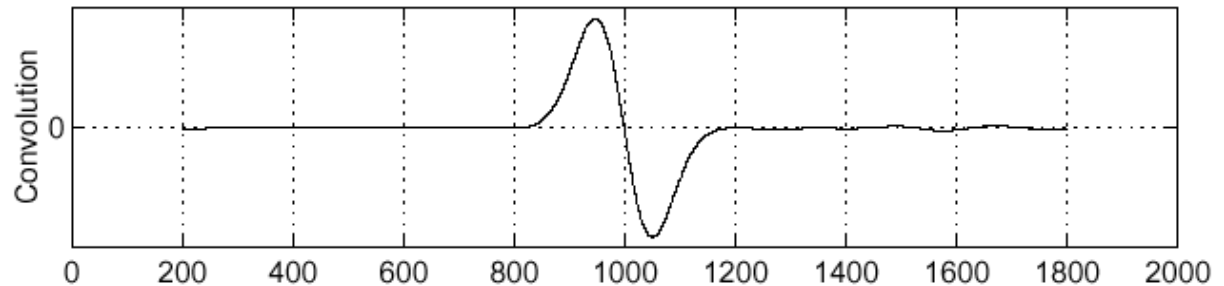
$f$



$\frac{\partial^2}{\partial x^2}h$



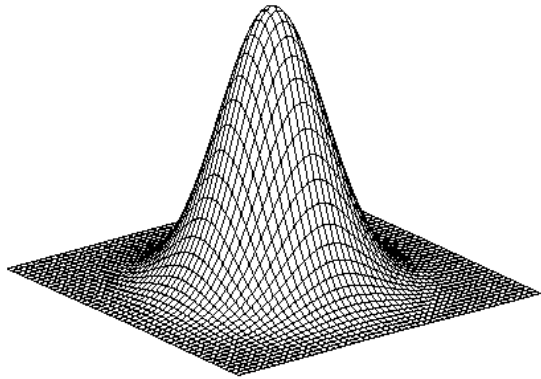
$(\frac{\partial^2}{\partial x^2}h) \star f$



Where is the edge?

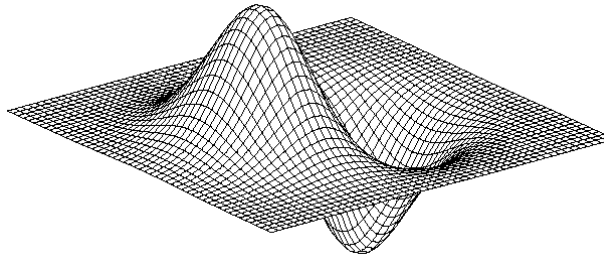
Zero-crossings of bottom graph

# 2D edge detection filters



Gaussian

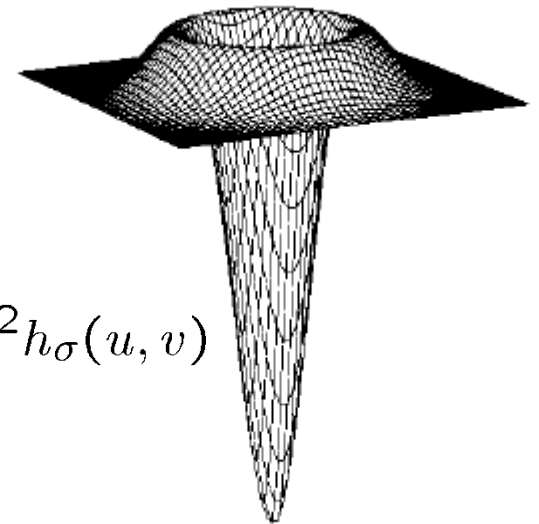
$$h_{\sigma}(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



derivative of Gaussian

$$\frac{\partial}{\partial x} h_{\sigma}(u, v)$$

Laplacian of Gaussian



$$\nabla^2 h_{\sigma}(u, v)$$



# Properties of Derivative Masks

- Coordinates of derivative masks have opposite signs in order to obtain a high response in regions of high contrast.
- The sum of coordinates of derivative masks is zero, so that a zero response is obtained on constant regions.
- First derivative masks produce high absolute values at points of high contrast.
- Second derivative masks produce zero-crossings at points of high contrast.

# **Approximating Intensity Edges with Polyline**

# **Approximating Intensity Edges with Polylines**

Once the intensity edges have been found, it is often desirable to approximate the edges with a more abstract representation such as line segments.

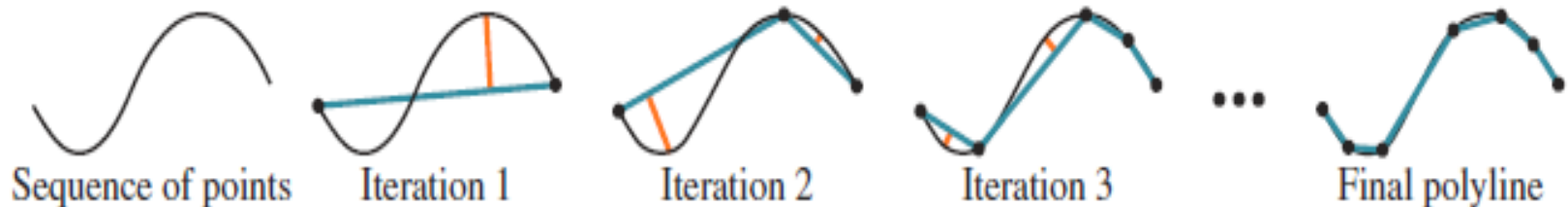
Purposes given a curve consisting of line segments (polylines), find a similar curve of fewer points.

# Approximating Intensity Edges with Polylines (cont.)

- The edgels are stored as an ordered sequence of points.
- An **anchor-floater line** is drawn from the first and last point.
- For each immediate points, its distance from the line is computed.
- If all distances are less than some threshold, then the immediate points are discarded.
- Otherwise the point with the with the maximum distance to the anchor-floater line is retained (**critical point**)
- The sequence is divided at the critical point, and the process is repeated for two new anchor-floater lines.
- This process continues recursively until all points are within the specified tolerance of the anchor-floater line.

# Douglas-Peucker Algorithm

- **Douglas-Peucker algorithm:** the classic algorithm for fitting a polyline to a sequence of points.



**Figure 7.13** The Douglas-Peucker algorithm recursively subdivides a polyline by computing the largest distance (orange line) from the points in the polyline to the anchor-floater lines (blue lines).

# **Features (Interest Points)**

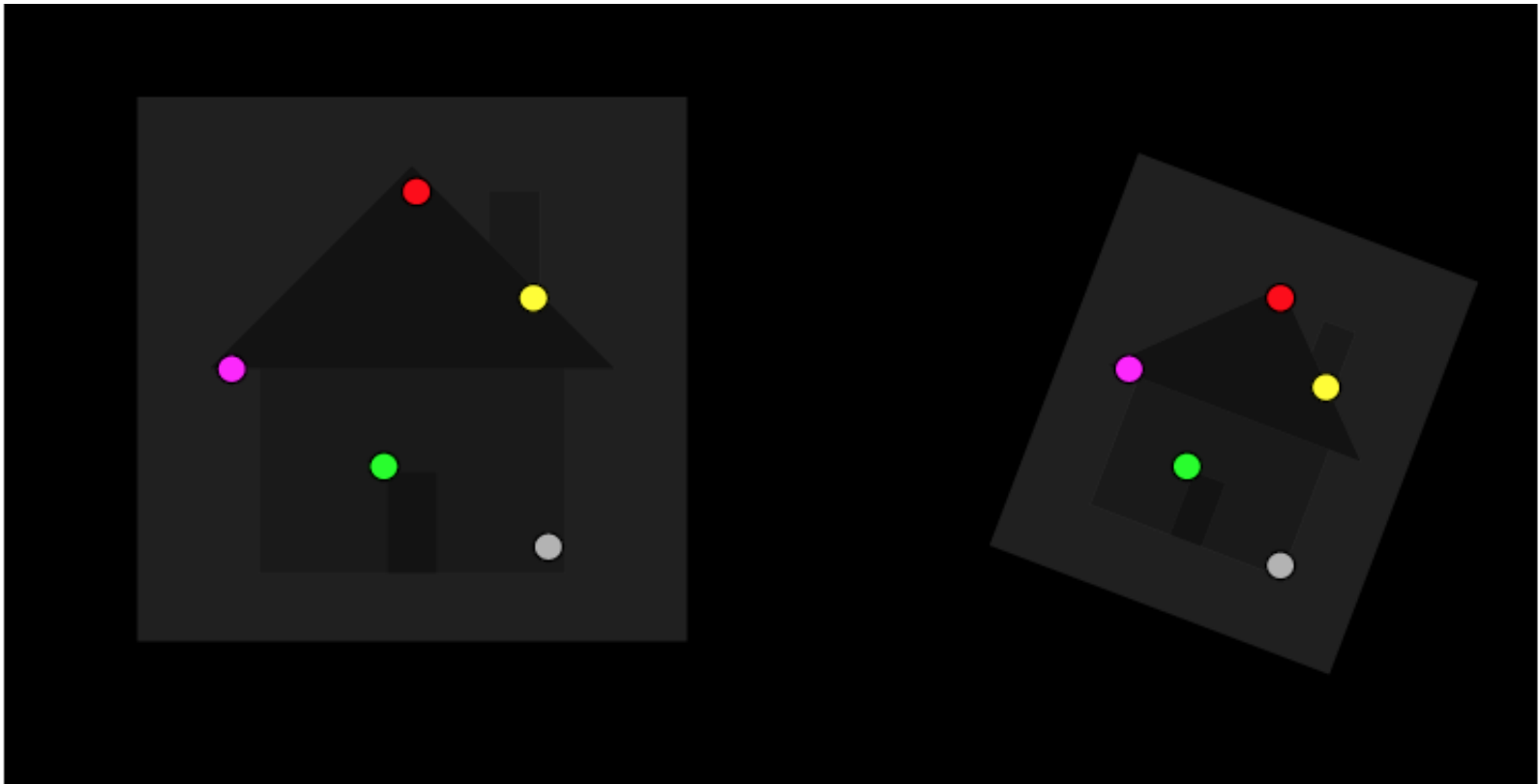
# Interests Points (Features)

**Definition:** Local features associated with a significant change of an image property or several properties simultaneously (e.g., intensity, texture, color).

## Motivations

- More robust features for use in matching
- Corresponding points (features) between images enable the estimation of parameters describing geometric transformations between the images.

# Interest Points (Features) cont.





# Desired properties for features (Interest Points)

- **Distinctive:** a single feature can be correctly matched with high probability.
- **Invariant:** invariant to transformations, illumination, and noise for robust matching across a substantial range of affine distortion, viewpoint change and so on. That is, it is repeatable.

# Interest Point Detection

- **Goal:** Find points in image that are stable across scaling, rotation, etc. (e.g. corner)
- A corner is characterized by a region with intensity change in two different directions.



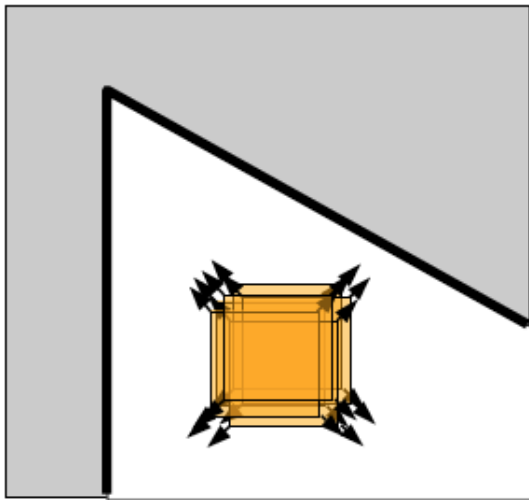
# Corners vs. Edges

- **Corners** are locations where variations of intensity function  $f(x,y)$  in both  $x$  and  $y$ .  
Both partial derivatives  $f_x$  and  $f_y$  are high.
- **Edges** are locations where variation of  $f(x,y)$  in certain directions is high, while variation in the orthogonal direction is low  
When edge is oriented along  $y$ ,  $f_x$  is large and  $f_y$  is small

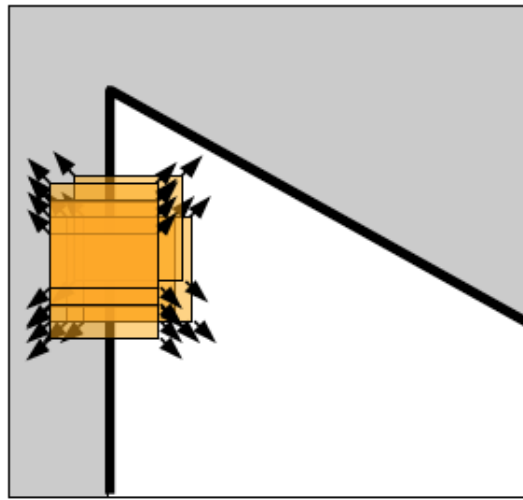
# Corner Detection: Basic Idea

We should easily recognize the point by looking through a small window.

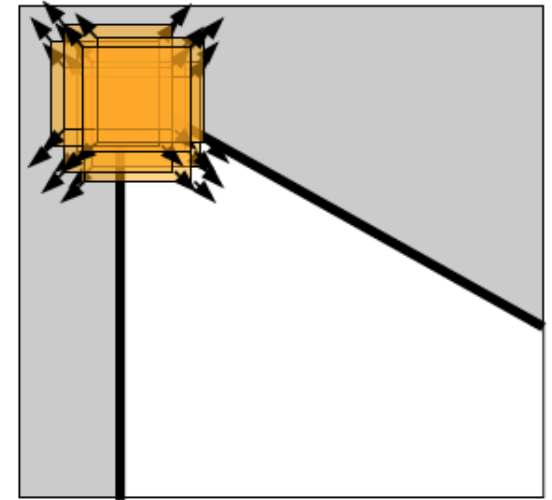
At a corner, shifting a window in any direction should give a large change in intensity.



“flat” region:  
no change in  
all directions



“edge”:  
no change along  
the edge direction



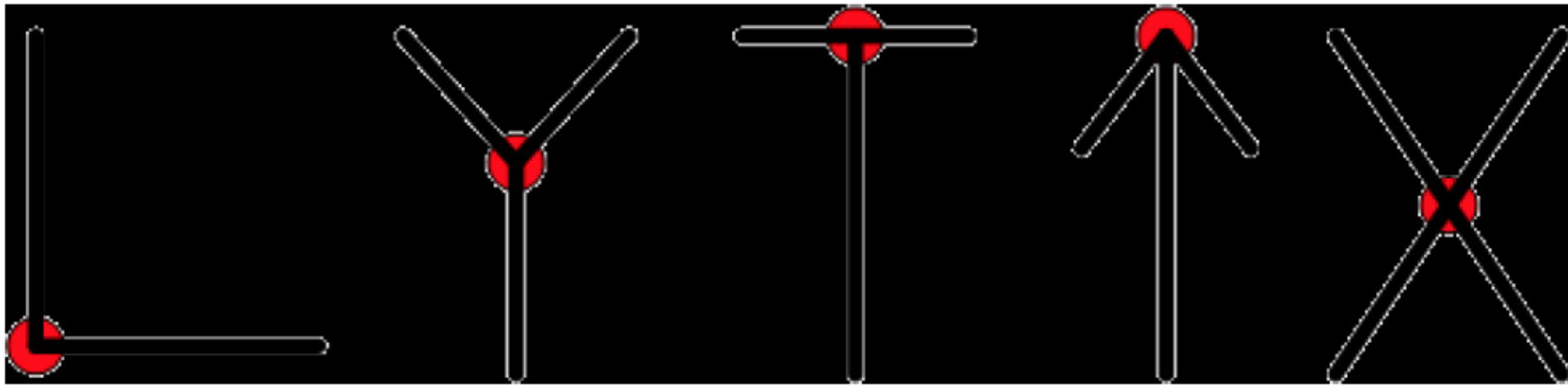
“corner”:  
significant change  
in all directions

# Main Steps in Corner Detection

- For each pixel in the image, the corner operator is applied to obtain a **cornerness** measure for this pixel.
- Threshold the cornerness map to eliminate weak corners
- Apply non-maximal suppression to eliminate points whose cornerness measure is not larger than the cornerness values of all points within a certain distance.

# Corner Types

- L-Junction, Y-Junction, T-Junction, Arrow-Junction, and X-Junction



# Moravec Interest Operator (1977)

- The Moravec operator shifts the pixels horizontally by a small amount and compares the difference between the original graylevel pattern and the shifted version.
- Then the process is repeated by shifting the pixels vertically by a small amount, comparing the difference in the same way.
- A small window is used (3x3 or 5x5) to shift in the eight principal directions.

# Moravec Interest Operator (cont.)

- The **sum of squared differences (SSD)** between the image patch and its shifted version:

$$\epsilon_{\mathcal{R}}(\Delta \mathbf{x}) \equiv \sum_{\mathbf{x} \in \mathcal{R}} (I(\mathbf{x}) - I(\mathbf{x} + \Delta \mathbf{x}))^2$$

- Moravec defines the **corneriness** of a pixel as the minimum SSD as the window is shifted left, right, up, and down:

$$\text{corneriness} \equiv \min \{ \epsilon_{\mathcal{R}}(-1, 0), \epsilon_{\mathcal{R}}(1, 0), \epsilon_{\mathcal{R}}(0, -1), \epsilon_{\mathcal{R}}(0, 1) \}, \quad (\text{Moravec})$$



# Moravec corner detector (cont.)

Change of intensity for the shift  $[u, v]$ :

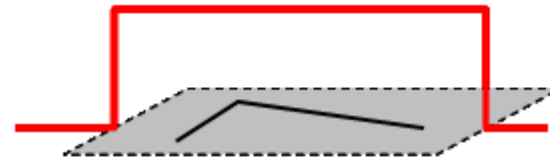
$$E(u, v) = \sum_{x, y} w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

Window  
function

Shifted  
intensity

Intensity

Window function  $w(x, y) =$



1 in window, 0 outside

Look for local maxima in  $\min\{E\}$

# Problems of Moravec detector

- Noisy response due to a binary window function
  - Only a set of shifts at every 45 degree is considered
  - Only minimum of  $E$  is taken into account
- ⇒ Harris corner detector (1988) solves these problems.

# Questions?

# Slide Credits

Presentation slides include those of:

Linda Shapiro, George Stockman, Simon Baker, Trevor Darrell, Cordelia Schmid, David Lowe, Darya Frolova, Denis Simakov, Robert Collins, Yung-Yu Chuang and Jiwon Kim