

# CMT107 Visual Computing Assignment Project Exam Help

https://tutorcs.com. Corner Detection

WeChat: cstutorcs

Xianfang Sun, Jing Wu

School of Computer Science and Informatics Cardiff University

#### Overview

- Feature Extraction
  - Characteristics of good features
  - Applications
- Corner Detection
  - Basic idea
  - Mathematics
- Harris Detector
- Invariance and Covariance

Assignment Project Exam Help

https://tutorcs.com

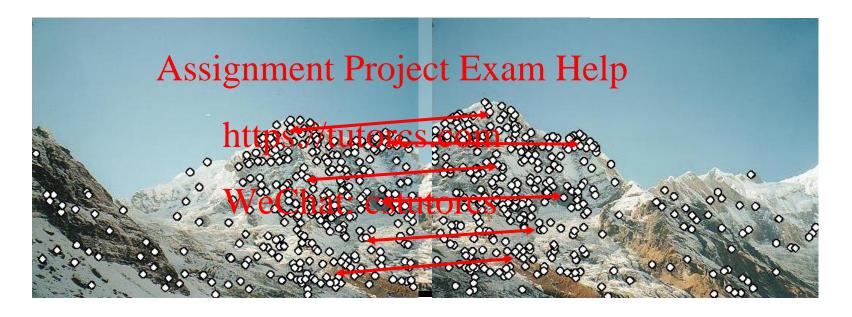
WeChat: cstutorcs

#### **Feature Extraction: Corners**



## Why Extract Features

- Motivation: panorama stitching
  - We have two images how do we combine them?



Step 1: extract features

Step 2: match features

Step 3: align images

#### Characteristics of Good Features



- Repeatability
  - The same feature can be found in several mages despite geometric and photometric transformations

    WeChat: cstutorcs
- Saliency
  - Each feature is distinctive
- Compactness and efficiency
  - Many fewer features than image pixels
- Locality
  - A feature occupies a relatively small area of the image; robust to clutter and occlusion

# **Applications**

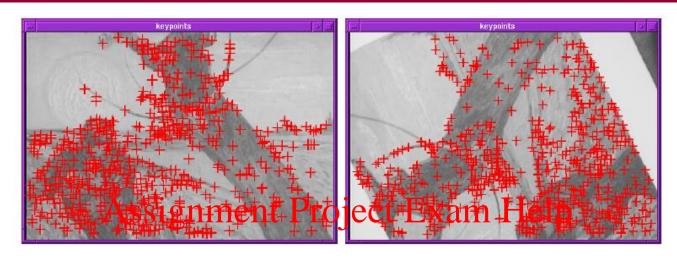
- Feature points are used for
  - Image alignment
  - 3D reconstruction
  - Motion tracking
  - Robot navigation Assignment Project Exam Help.
  - Indexing and database retrieval
  - Object recognition

https://tutorcs.com





# Finding Corners



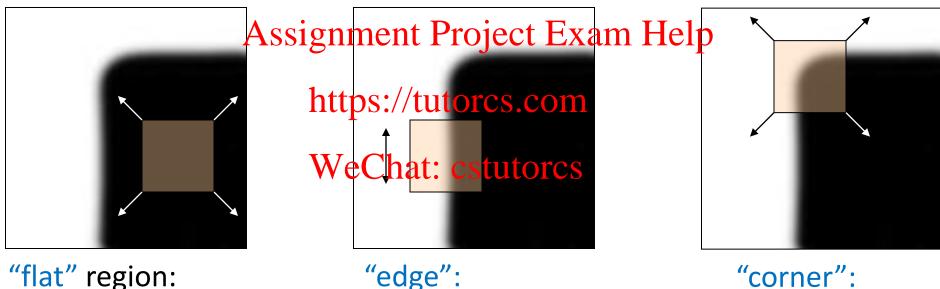
https://tutorcs.com

- Key properties: In the region around a corner, image gradient has two or more dominant directions WeChat: cstutorcs
- Corners are repeatable and distinctive

C.Harris and M.Stephens. "A Combined Corner and Edge Detector." Proceedings of the 4th Alvey Vision Conference, 1988: pages 147--151.

#### Corner Detection: Basic Idea

- We can easily recognise the point by looking through a small window
- Shifting a window in any direction should give a large change in intensity



"flat" region: no change in all directions

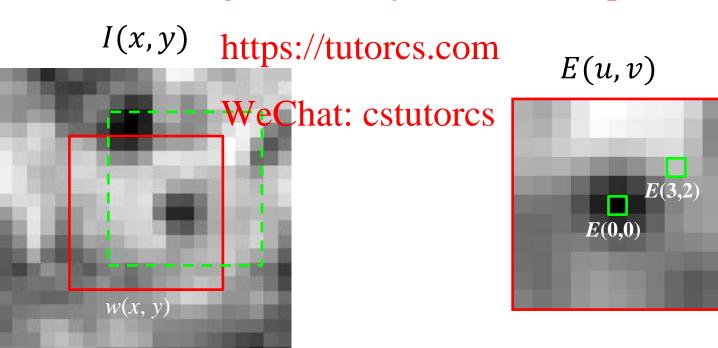
no change along the edge direction

significant change in all directions

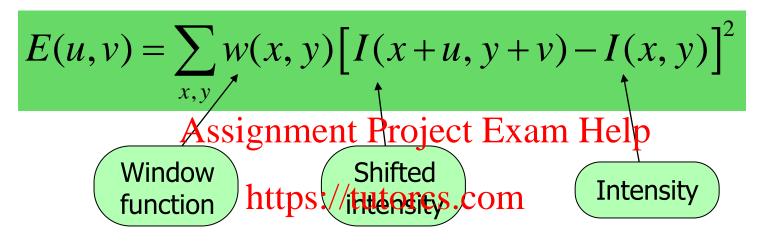
• Change of intensity for the shift [u, v]

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

Assignment Project Exam Help



• Change of intensity for the shift [u, v]



WeChat: cstutorcs

• Window function 
$$w(x,y) = 0$$
 or  $1$  in window,  $0$  outside Gaussian

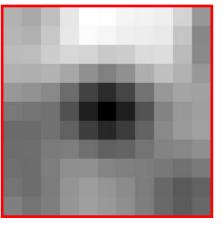
• Change of intensity for the shift [u, v]

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

Assignment Project Exam Help

• We want to find out how this function behaves for small shifts https://tutorcs.com

WeChate Cystutores



• Change of intensity for the shift [u, v]

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

- Assignment Project Exam Help
   We want to find out how this function behaves for small shifts
- Using first-order Taylor apphibles the second  $I(x+u,y+v) \approx I(x,y) + U(x)(x,y) + U(x)(x,y)$ . Then:

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

$$= \sum_{x,y} w(x,y) [uI_x(x,y) + vI_y(x,y)]^2 = \cdots$$

The approximation simplifies to

$$E(u,v) \approx [u \ v] \ M \begin{bmatrix} u \\ v \end{bmatrix}$$
  
Assignment Project Exam Help

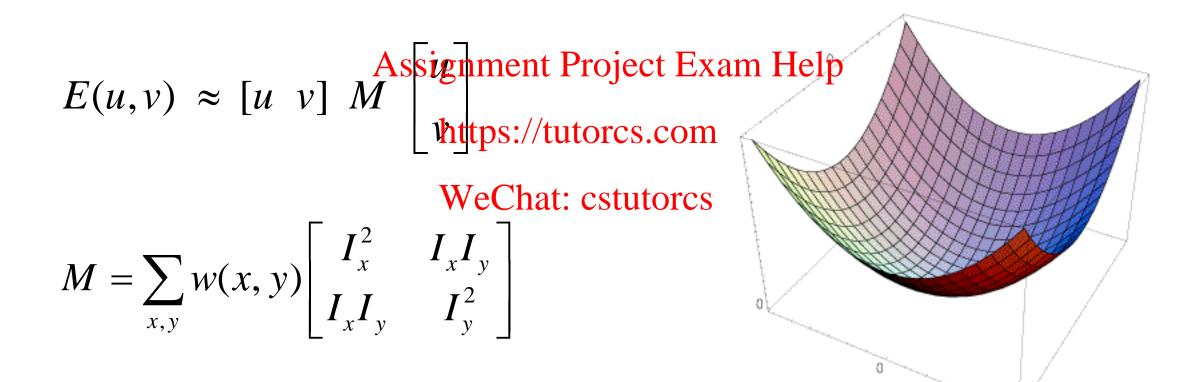
https://tutorcs.com

• where M is a second moment matrix computed from image derivatives:

WeChat: cstutorcs
$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

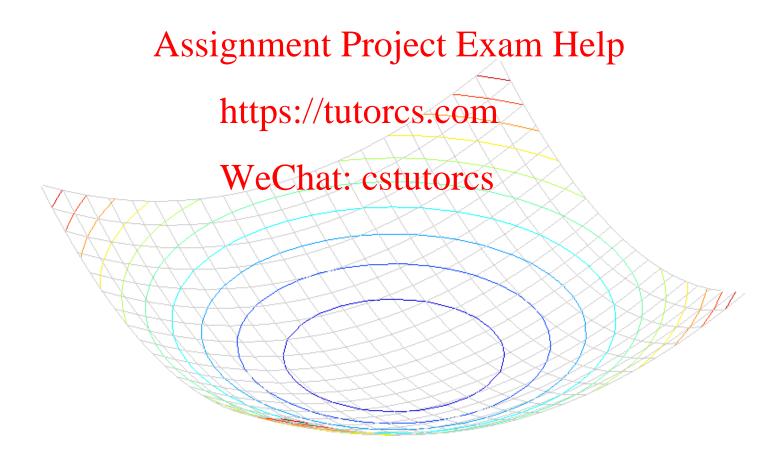
# Interpreting the Second Moment Matrix

• The surface E(u,v) is locally approximated by a quadratic form. Let's try to understand its shape.



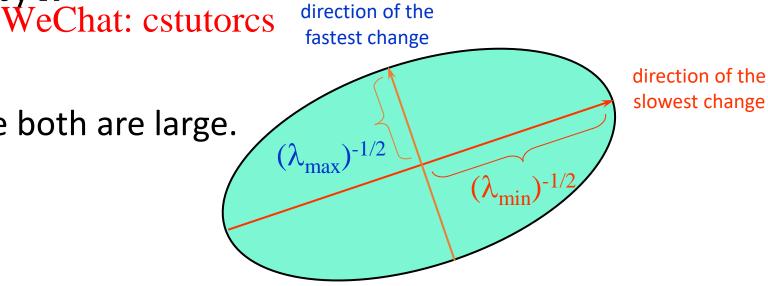
# Interpreting the Second Moment Matrix

- Consider a horizontal slice of E(u, v):  $\begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix} = const$
- This is an equation of an ellipse

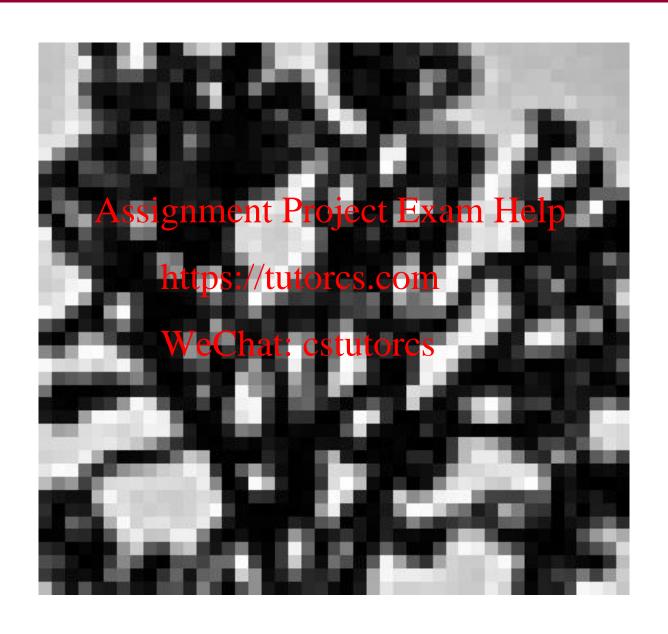


# Interpreting the Second Moment Matrix

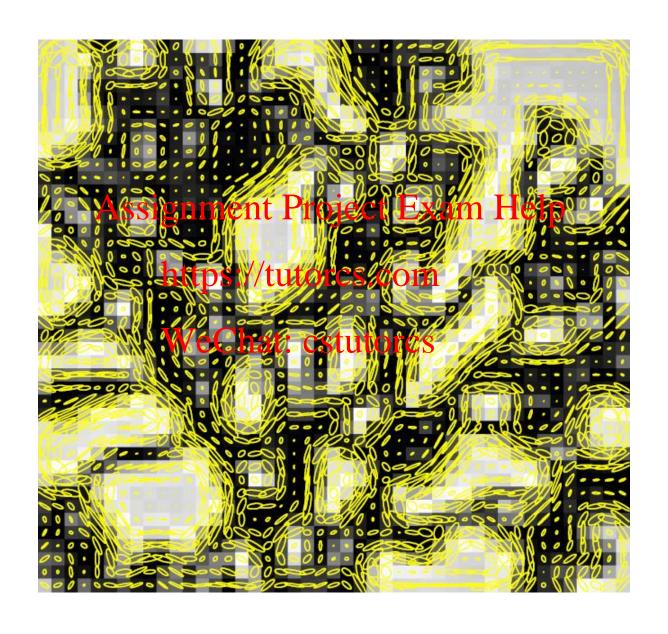
- Consider a horizontal slice of E(u, v):  $\begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix} = const$
- This is an equation of an ellipse
- Diagonalization of M:  $M = R^{-1}$   $\lambda_1$   $\lambda_1$   $\lambda_2$   $\lambda_3$   $\lambda_4$   $\lambda_5$   $\lambda$
- The axis lengths are determined by R
- If either  $\lambda$  is close to 0, then this is not a corner, so look for positions where both are large.



#### Visualization of Second Moment Matrices

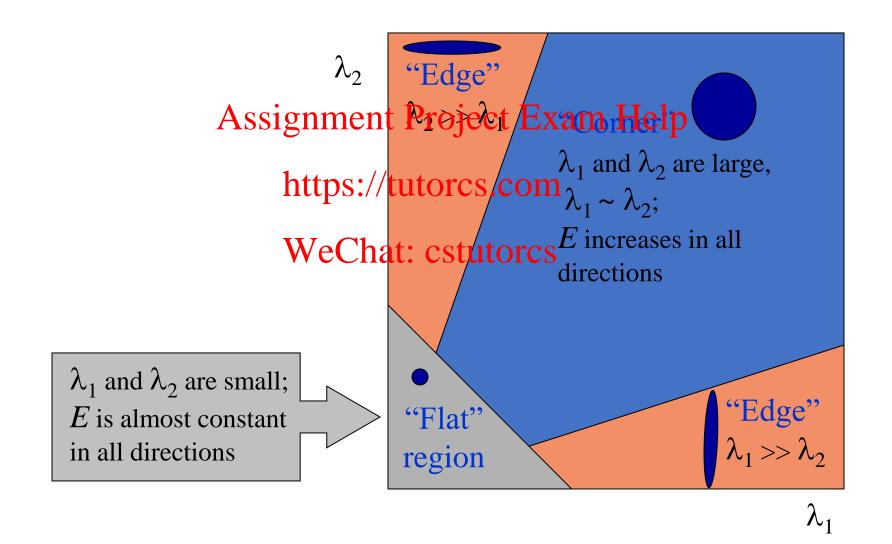


# Visualization of Second Moment Matrices



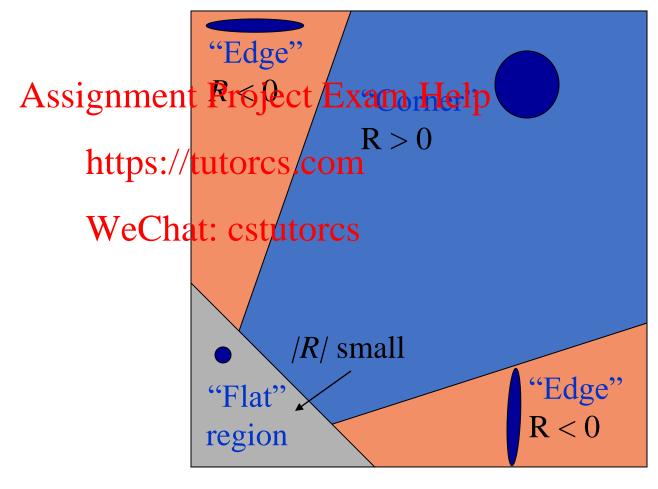
# Interpreting the Eigen Values

• Classification of image points using eigenvalues of *M*.



## Corner Response function

•  $R = \lambda_1 \lambda_2 - \alpha (\lambda_1 + \lambda_2)^2 = \det(M) - \alpha \operatorname{trace}(M)^2$  $\alpha$ : constant (0.04 to 0.15)



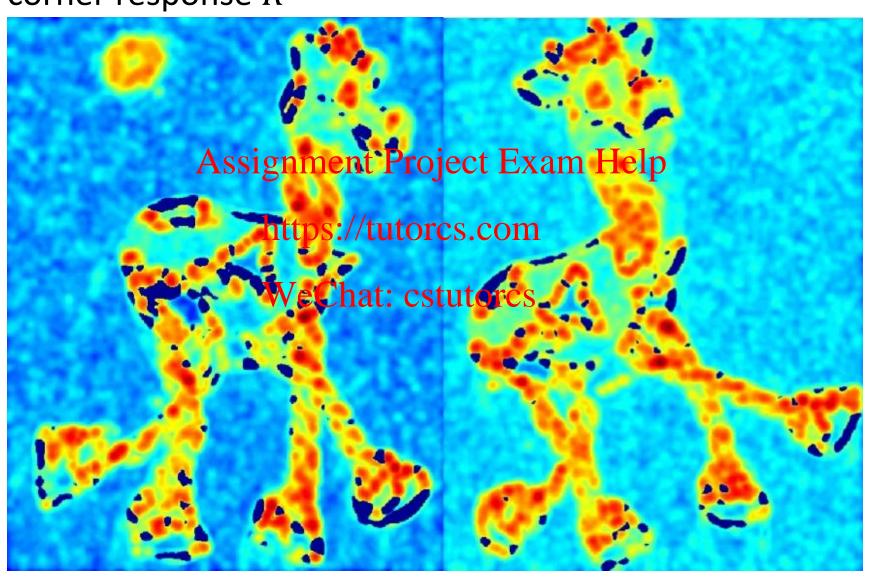
- Compute Gaussian derivatives at each pixel
- ullet Compute second moment matrix M in a Gaussian window around each pixel
- Computer corner response function *R*
- Threshold R Assignment Project Exam Help
- Find local maxima of response function (nonmaximum suppression) https://tutorcs.com

WeChat: cstutorcs

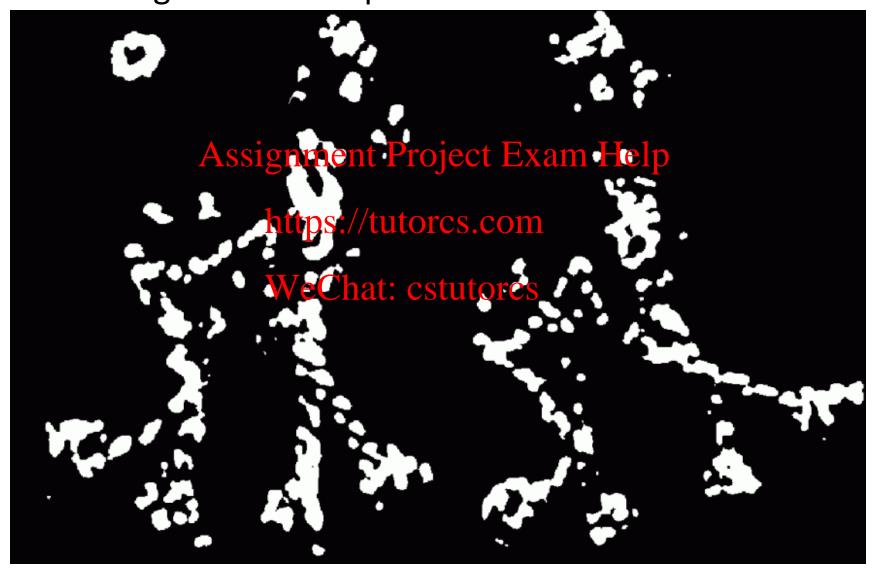
C.Harris and M.Stephens. "A Combined Corner and Edge Detector." Proceedings of the 4th Alvey Vision Conference: pages 147—151, 1988.



• Compute corner response *R* 



• Find points with larger corner response: R > threshold



• Take the points of local maxima of *R* 





- We want corner locations to be *invariant* to photometric transformations, and *covariant* to geometric transformations.
  - Invariance: image is transformed and corner locations do not change
  - Covariance: if we have two transformed versions of the same image, features should be detected in corresponding location ject Exam Help

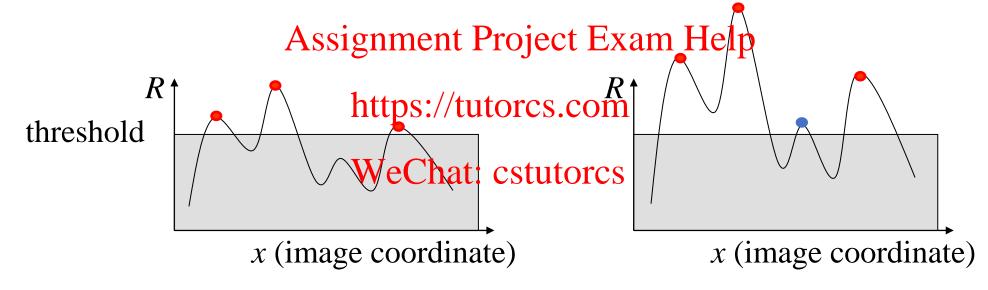


# Affine Intensity Change

• 
$$I \rightarrow aI + b$$

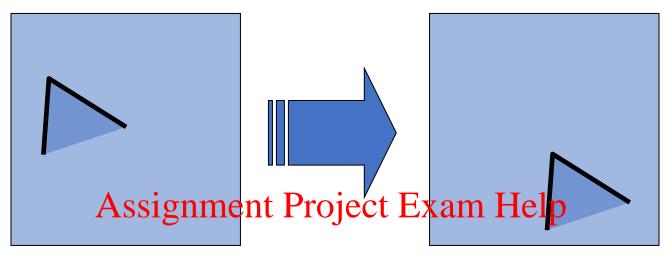


- Only derivatives are used  $\Rightarrow$  invariance to intensity shift  $I \rightarrow I + b$
- Intensity scaling:  $I \rightarrow aI$



Partially invariant to affine intensity change

# **Image Translation**

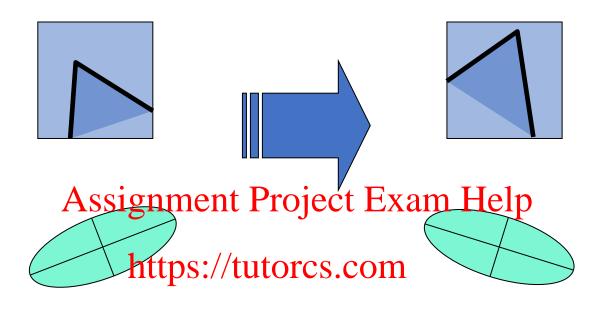


https://tutorcs.com

• Derivatives and window function are shift-invariant WeChat: cstutorcs

Corner location is covariant w.r.t. translation

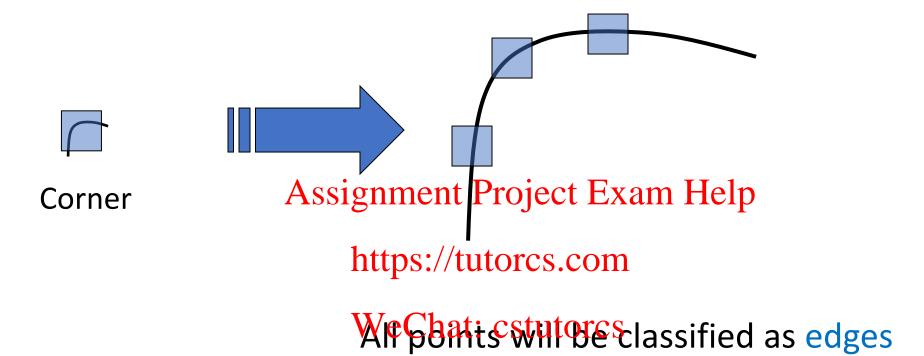
#### **Image Rotation**



• Second moment ellipse rotates, but its shape (i.e., eigenvalues) remains the same

Corner location is covariant w.r.t. rotation

# Scaling



Corner location is not covariant to scaling!

## Summary

- Why we need feature extraction? What are the applications of feature extraction?
- What are the characteristics of good features?
- Describe the basic idea of corner detection Assignment Project Exam Help
- How to decide whether a point is in a flat region, on an edge, or a corner according to the two eigen belows by the second moment matrix?
- Describe the steps of Harrisydetectors
- What is Invariance and Covariance?
- Is affine intensity change invariant? Is image translation, rotation, scaling covariant?