#### ME6406 Machine Vision

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Part 2D:
Detection of dominant points on plane curve

http://kmlee.gatech.edu/me6406

1

### **Contents**

#### ☐ Detection of dominant points on plane curve

- **+** Curvature
- Scale-space filtering
- ♦ Scale space description of corner

In Canvas ("Reading materials" folder)

A. Rattarangsi and T. R. Chin, "Scale-based Detection of corners and planar curves," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 14, no 4m April 1992.

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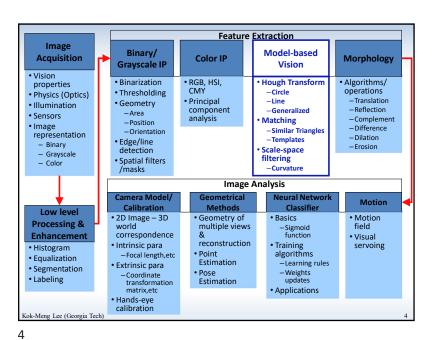
3

# **Course Outline**

- Introduction and low-level processing
  - Physics of digital images, histogram equalization, segmentation, edge detection, linear filters.
- Model-based Vision
  - Hough transform, pattern representation, matching
- · Geometric methods
  - Camera model, calibration, pose estimation
- · Neural network for machine vision
  - Basics, training algorithms, and applications
- · Color images and selected topics
  - Physics, perception, processing and applications

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2

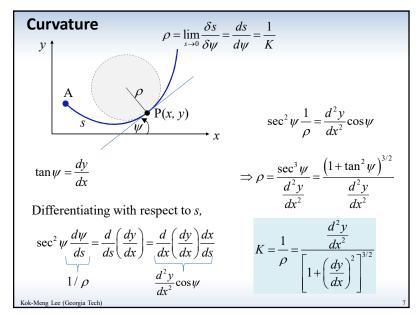


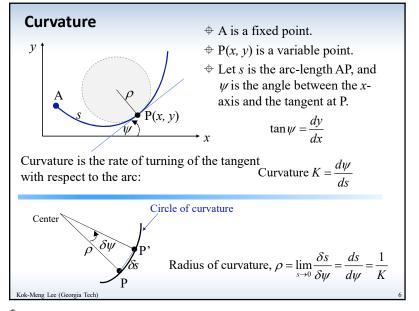
☐ Detection of dominant points on plane curve

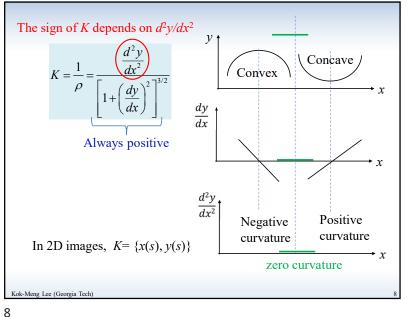
- **+** Curvature
- + Scale space description of corner

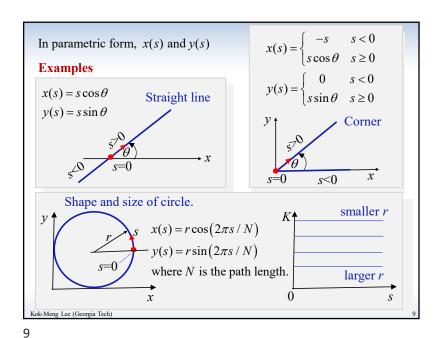
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5









☐ Detection of dominant points on plane curve

- Scale-space filtering

In parametric form,

x(s);  $\dot{x} = \frac{dx}{ds}$  and  $\ddot{x} = \frac{d^2x}{ds^2}$ 

Similarly,

$$y(s)$$
;  $\dot{y} = \frac{dy}{ds}$  and  $\ddot{y} = \frac{d^2y}{ds^2}$ 

$$y' = \frac{\dot{y}}{\dot{x}}$$
 where  $y' = \frac{dy(s)}{dx(s)}$ 

$$y'' = \frac{d^2y}{dx^2} = \frac{\dot{x}\ddot{y} - \dot{y}\ddot{x}}{\dot{x}^3}$$

Recall  $K(s) = \frac{y''}{\left[1 + (y')^2\right]^{3/2}}$ 

$$=\frac{\frac{\dot{x}\ddot{y}-\dot{y}\ddot{x}}{\dot{x}^3}}{\left[1+\left(\frac{\dot{y}}{\dot{x}}\right)^2\right]^2}$$

Thus.

$$y' = \frac{\dot{y}}{\dot{x}}$$
 where  $y' = \frac{dy(s)}{dx(s)}$ 

$$y'' = \frac{d^2y}{dx^2} = \frac{\dot{x}\ddot{y} - \dot{y}\ddot{x}}{\dot{x}^3}$$

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10

Scale-space filtering method

Let  $g_{\sigma}(s) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(\frac{-s^2}{2\sigma^2}\right)$  be the Gausspan filter.

Smoothing the curve with  $g_{\sigma}(s)$  is the same as convolving with x(s) and y(s). Mathematically,

$$X(s,\sigma) = x * g_{\sigma} = \int_{-\infty}^{\infty} x(s-u)g_{\sigma}(u)du$$
$$Y(s,\sigma) = y * g_{\sigma} = \int_{-\infty}^{\infty} y(s-u)g_{\sigma}(u)du$$

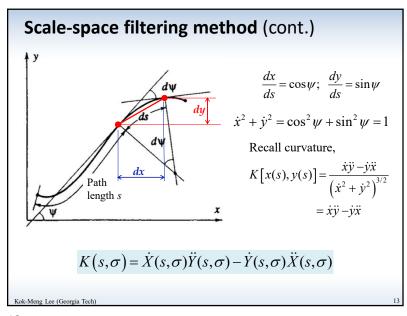
 $X(s, \sigma)$  and  $Y(s, \sigma)$  are the x and y coordinates of the smoothed curve, respectively; and \* is the convolution operator.

Recall curvature,  $K[x(s), y(s)] = \frac{\dot{x}\ddot{y} - \dot{y}\ddot{x}}{\left(\dot{x}^2 + \dot{y}^2\right)^{3/2}}$ where  $\dot{X} = \frac{\partial X}{\partial s}, \dot{Y} = \frac{\partial Y}{\partial s}, \ddot{X} = \frac{\partial^2 X}{\partial s^2}, \ddot{Y} = \frac{\partial^2 Y}{\partial s^2}$ 

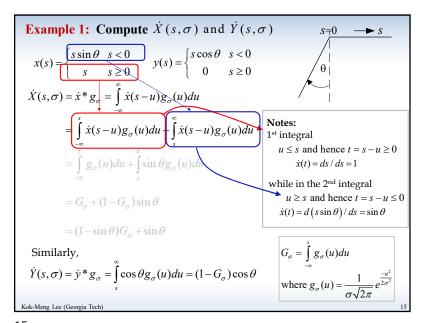
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11



13



Scale-space filtering method (cont.)

Let  $F(s, \sigma)$  represents the function,  $X(s, \sigma)$  or  $Y(s, \sigma)$ ; and

F(s, 0) is the unsmooth coordinates, x(s) and y(s), respectively.

$$F(s,\sigma) = \int_{-\infty}^{\infty} f(s-u)g_{\sigma}(u)du = \int_{-\infty}^{\infty} g_{\sigma}(s-u)f(u)du$$
$$f * g_{\sigma} = g_{\sigma} * f$$

$$\frac{dF(s,\sigma)}{ds} = \frac{d}{ds} (f * g_{\sigma}) = \int_{-\infty}^{\infty} \frac{df(s-u)}{ds} g_{\sigma}(u) du = \int_{-\infty}^{\infty} \frac{dg_{\sigma}(s-u)}{ds} f(u) du$$
$$\dot{F}(s,\sigma) = \frac{d(F(s,0) * g_{\sigma})}{ds} = \frac{dF(s,0)}{ds} * g_{\sigma}$$

Discrete approximation: 
$$F(s,\sigma) = f * g_{\sigma} = \sum_{u=-5\sigma}^{5\sigma} f(s-u)g_{\sigma}(u)$$

$$\frac{dF(s,\sigma)}{ds} \approx F(j+1,\sigma) - F(j-1,\sigma); \quad \frac{d^2F(s,\sigma)}{ds^2} \approx F(j+1,\sigma) - 2F(j) + F(j-1,\sigma)$$

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14

Example 2: Compute 
$$X(s,\sigma)$$
 and  $Y(s,\sigma)$ 

$$x(s) = \begin{cases} s\sin\theta & s < 0 \\ s & s \ge 0 \end{cases} \quad y(s) = \begin{cases} s\cos\theta & s < 0 \\ 0 & s \ge 0 \end{cases}$$

$$X(s,\sigma) = x * g_{\sigma} = \int_{-\infty}^{\infty} x(\underbrace{s-u})g_{\sigma}(u)du$$

$$= \int_{-\infty}^{s} \underbrace{(s-u)}_{u \le s, t = s-u \ge 0} g_{\sigma}(u)du + \int_{s}^{\infty} \underbrace{(s-u)\sin\theta}_{u > s, t = s-u < 0} g_{\sigma}(u)du$$

$$= s \int_{-\infty}^{s} g_{\sigma}(u)du + s\sin\theta \int_{s}^{\infty} g_{\sigma}(u)du - \int_{-\infty}^{s} ug_{\sigma}(u)du - \sin\theta \int_{s}^{\infty} ug_{\sigma}(u)du$$

$$= Recall: G_{\sigma} = \int_{-\infty}^{s} g_{\sigma}(u)du \text{ where } g_{\sigma} = \frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-s^{2}}{2\sigma^{2}}}$$

$$X(s,\sigma) = sG_{\sigma} + s\sin\theta \left(1 - G_{\sigma}\right) - \int_{-\infty}^{s} ug_{\sigma}(u)du - \sin\theta \int_{s}^{\infty} ug_{\sigma}(u)du$$
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Example 2 (cont.): Let 
$$\tau = \frac{-u^2}{2\sigma^2} \Rightarrow du = -\frac{\sigma^2 d\tau}{u}$$

$$-\int ug_{\sigma}(u)du = -\int u\left[\frac{e^r}{\sigma\sqrt{2\pi}}\right]\left(-\frac{\sigma^2 d\tau}{u}\right) = \frac{\sigma^2}{\sigma\sqrt{2\pi}}\int e^r d\tau = \sigma^2 g_{\sigma}(u)$$
Since  $g_{\sigma}(u \to \pm \infty) = \left[\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-u^2}{2\sigma^2}}\right]_{u \to \pm \infty} = 0$ 

$$\Rightarrow -\int_{-\infty}^{s} ug_{\sigma}(u)du = \sigma^2 g_{\sigma}(u)\Big|_{-\infty}^{s} = \sigma^2 g_{\sigma}(s)$$
and  $-\int_{s}^{\infty} ug_{\sigma}(u)du = \sigma^2 g_{\sigma}(u)\Big|_{-\infty}^{s} = -\sigma^2 g_{\sigma}(s)$ 

$$X(s,\sigma) = sG_{\sigma} + s\left(1 - G_{\sigma}\right)\sin\theta - \int_{-\infty}^{s} ug_{\sigma}(u)du - \sin\theta\int_{s}^{\infty} ug_{\sigma}(u)du$$

$$= sG_{\sigma} + s\left(1 - G_{\sigma}\right)\sin\theta + \sigma^2\left(1 - \sin\theta\right)g_{\sigma}(s)$$

17

Example 3:  $\dot{X}(s,\sigma)$  and  $\dot{Y}(s,\sigma)$  can be derived from the derivative of  $X(s,\sigma)$  and  $Y(s,\sigma)$ .  $X(s,\sigma) = s \left[ (1-\sin\theta)G_{\sigma} + \sin\theta \right] + \sigma^{2} (1-\sin\theta)g_{\sigma}(s) \\
Y(s,\sigma) = \cos\theta \left[ s(1-G_{\sigma}) - \sigma^{2}g_{\sigma}(s) \right]$   $\dot{X}(s,\sigma) = \left[ (1-\sin\theta)G_{\sigma} + \sin\theta \right] + s \frac{d}{ds} \left[ (1-\sin\theta)G_{\sigma} + \sin\theta \right] + \sigma^{2} (1-\sin\theta) \frac{dg_{\sigma}(s)}{ds}$   $\dot{Y}(s,\sigma) = \cos\theta \left[ (1-G_{\sigma}) + s \frac{\partial}{\partial s} (1-G_{\sigma}) - \sigma^{2} \frac{dg_{\sigma}(s)}{ds} \right]$ where  $\frac{dg_{\sigma}(s)}{ds} = \frac{1}{\sigma\sqrt{2\pi}} \frac{de^{-s^{2}/(2\sigma^{2})}}{ds} = \frac{1}{\sigma\sqrt{2\pi}} \left[ e^{-s^{2}/(2\sigma^{2})} \left( \frac{-\mathcal{Z}s}{\mathcal{Z}\sigma^{2}} \right) \right] = -\frac{sg_{\sigma}(s)}{\sigma^{2}}$   $\dot{X}(s,\sigma) = (1-\sin\theta)G_{\sigma} + \sin\theta + s(1-\sin\theta)g_{\sigma} - s(1-\sin\theta)g_{\sigma} = (1-\sin\theta)G_{\sigma} + \sin\theta$   $\dot{Y}(s,\sigma) = \cos\theta \left[ (1-G_{\sigma}) + s(-g_{\sigma}) - \sigma^{2}(-\frac{sg_{\sigma}}{\sigma^{2}}) \right] = (1-G_{\sigma})\cos\theta$   $\dot{X}(s,\sigma) = (1-\sin\theta)G_{\sigma} + \sin\theta \quad \text{and} \quad \dot{Y}(s,\sigma) = (1-G_{\sigma})\cos\theta$ Same as Example 1

Example 2 (cont.):

Similarly, 
$$Y(s, \sigma) = y * g_{\sigma} = \int_{-\infty}^{\infty} y(s-u)g_{\sigma}(u)du$$
  

$$= \int_{s}^{\infty} (s-u)\cos\theta g_{\sigma}(u)du$$

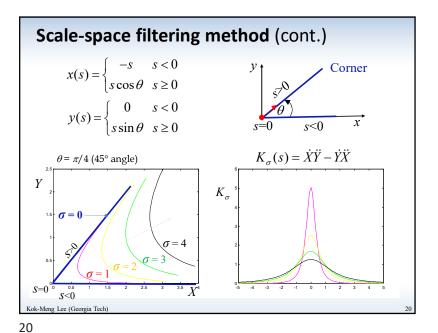
$$= \cos\theta \left[ s \int_{s}^{\infty} g_{\sigma}(u)du - \int_{s}^{\infty} ug_{\sigma}(u)du \right]$$

$$= \cos\theta \left[ s(1-G_{\sigma}) - \sigma^{2}g_{\sigma}(s) \right]$$

$$X(s,\sigma) = s \Big[ (1 - \sin \theta) G_{\sigma} + \sin \theta \Big] + \sigma^{2} (1 - \sin \theta) g_{\sigma}(s)$$

$$Y(s,\sigma) = \cos \theta \Big[ s(1 - G_{\sigma}) - \sigma^{2} g_{\sigma}(s) \Big]$$

18



## ☐ Detection of dominant points on plane curve

- ♦ Scale space description of corner

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21

# Scale space curvature optimization

$$K(s,\sigma) = \dot{X}(s,\sigma)\ddot{Y}(s,\sigma) - \dot{Y}(s,\sigma)\ddot{X}(s,\sigma)$$

$$\frac{dK}{ds} = \frac{d(\dot{X}\ddot{Y} - \dot{Y}\ddot{X})}{ds} = \dot{X}\ddot{Y} + \underbrace{\ddot{X}\ddot{Y} - (\ddot{X}\ddot{Y} + \dot{Y}\ddot{X})}_{\text{cancel out}} = 0$$

$$\frac{\partial K}{\partial s} = \dot{X}(s,\sigma)\ddot{Y}(s,\sigma) - \dot{Y}(s,\sigma)\ddot{X}(s,\sigma) = 0$$

Recall:  $F(s, \sigma)$  represents the function,  $X(s, \sigma)$  or  $Y(s, \sigma)$ ; and

F(s, 0) is the unsmooth coordinates, x(s) and y(s), respectively.

$$\ddot{F}(s,\sigma) = \frac{d^3}{ds^3} \Big[ F(s,0) * g_{\sigma}(s) \Big] = \ddot{F}(s,0) * \dot{g}_{\sigma}(s) = \dot{F}(s,0) * \ddot{g}_{\sigma}(s)$$

where 
$$\frac{dg_{\sigma}(s)}{ds} = -\frac{sg_{\sigma}(s)}{\sigma^2}$$

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# **Curvature optimization for locating maxima**

$$K(s,\sigma) = \dot{X}(s,\sigma)\ddot{Y}(s,\sigma) - \dot{Y}(s,\sigma)\ddot{X}(s,\sigma)$$

- $\Box$  Given the scale parameter  $\sigma$ , solve for all the locations that have maximum absolute curvature  $|K(s, \sigma)|$ , which are the positive maxima (concave) or negative maxima (convex).
- $\square$  Apply curvature optimization (treating  $\sigma$  as a given constant),
  - $\Phi$  For  $K(s, \sigma) > 0$ , solve for the solutions  $\{s_i\}$  in  $\frac{d}{ds}K[X(s,\sigma),Y(s,\sigma)] = 0 \text{ subject to } \frac{d^2}{ds^2}K[X(s,\sigma),Y(s,\sigma)] < 0$
  - $\Phi$  For  $K(s, \sigma) < 0$ , solve for the solutions  $\{s_i\}$  in  $\frac{d}{ds}K[X(s,\sigma),Y(s,\sigma)] = 0$  subject to  $\frac{d^2}{ds^2}K[X(s,\sigma),Y(s,\sigma)] > 0$

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22

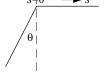
# Scale space description of corner

$$K_{\sigma}(X,Y) = \dot{X}\ddot{Y} - \dot{Y}\ddot{X}$$

Scale-space curvature optimization

$$\partial K(X,Y)/\partial s=0$$

$$\dot{X}(s,\sigma)\ddot{Y}(s,\sigma) - \dot{Y}(s,\sigma)\ddot{X}(s,\sigma) = 0$$



$$\begin{split} \dot{X}(s,\sigma) &= (1-\sin\theta)G_{\sigma} + \sin\theta & \dot{Y}(s,\sigma) &= (1-G_{\sigma})\cos\theta \\ \ddot{X}(s,\sigma) &= (1-\sin\theta)g_{\sigma} & \ddot{Y}(s,\sigma) &= -g_{\sigma}\cos\theta \\ \ddot{X}(s,\sigma) &= (1-\sin\theta)\dot{g}_{\sigma} & \ddot{Y}(s,\sigma) &= -\dot{g}_{\sigma}\cos\theta \end{split}$$

$$\begin{split} & \big[ (1-\sin\theta)G_{\sigma} + \sin\theta \big] \big( -\dot{g}_{\sigma}\cos\theta \big) - \big[ (1-G_{\sigma})\cos\theta \big] (1-\sin\theta)\dot{g}_{\sigma} = 0 \\ & \big[ -\dot{g}_{\sigma}\cos\theta (1-\sin\theta)G_{\sigma} - \dot{g}_{\sigma}\cos\theta\sin\theta \big] \end{split}$$

 $+\dot{g}_{\sigma}\cos\theta(1-\sin\theta)G_{\sigma}+\dot{g}_{\sigma}\cos\theta\sin\theta]-\dot{g}_{\sigma}\cos\theta=0 \qquad \left|-\dot{g}_{\sigma}\cos\theta=0\right|$ 

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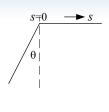
24

# Scale space description of corner

$$-\dot{g}_{\sigma}\cos\theta=0$$

 $\Phi$  At 0 = 90°, it becomes a straight line.

In this case, any solution s will satisfy (\*) but not the constraint of  $\frac{d^2K(s,\sigma)}{ds^2} > 0$ 

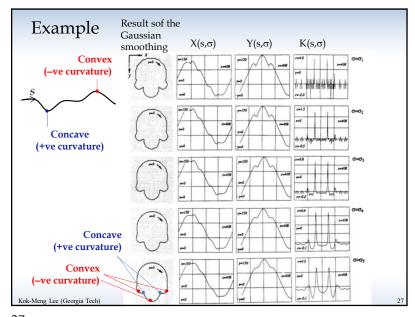


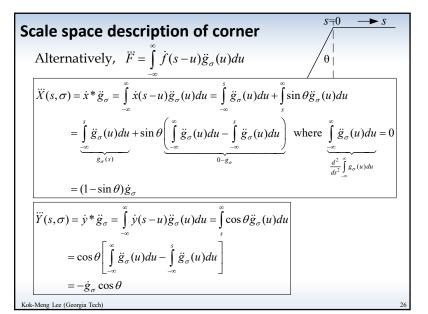
Hence, there is no absolute maximum.

- $\Phi$  In the case of  $0 > -90^{\circ}$  but not equal to  $90^{\circ}$ ,  $\dot{g}_{\sigma} = 0^{\circ}$ 
  - Therefore, the only solution is at s = 0 independent of the corner angle **0**, and the scale parameter  $\sigma$ .
  - This produces a vertical line in scale space, that is, the absolute maxima occur at the same contour location independent of smoothing.

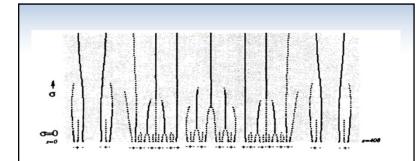
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25





26



## Example

Scale space map of maxima of absolute curvature. The horizontal axis is the arc length of the curve at  $\sigma$ = 0. The vertical axis is the Gaussian function parameter D determining the degree of smoothing. The line pattern in the map represents the locations of the local maxima of the curvature. A +sign indicates downward concavity, and a - sign indicates upward concavity.

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# The curvature method

- 1. Find the outside boundary bwboundaries(~BW, 'noholes')
- 2. Gaussian smoothing conv.m
- 3. Calculate curvature

$$K(s) = \dot{X}(s)\ddot{Y}(s) - \ddot{Y}(s)\dot{X}(s)$$

$$(s) \cong diff(X), \ \dot{Y}(s) \cong diff(Y)$$

$$(s) \cong diff(\dot{X}), \ \ddot{Y}(s) \cong diff(\dot{Y})$$

