

# Medical Image Analysis and Processing

## Medical Image Segmentation Deformable Model - Parametric

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Distance/online Course: Session 20 Episode#2

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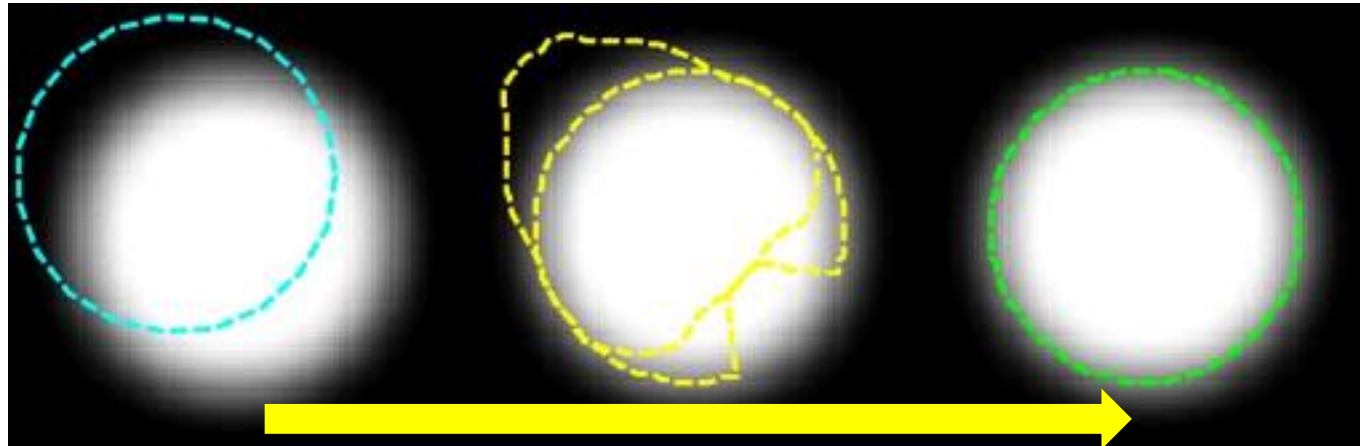
- › Introduction to Deformable Models
- › Parametric Deformable Model
- › Internal Forces
- › External Forces

# Definition

- › A *deformable* model (curve or surface) is a geometric object whose shape can *change* over *time*.
- › Deformable models move under the influence of the *model* itself and from the *image* data.
- › The internal and external effects are defined so that the model will conform to an object boundary or other desired features within an image.

## General Perspective:

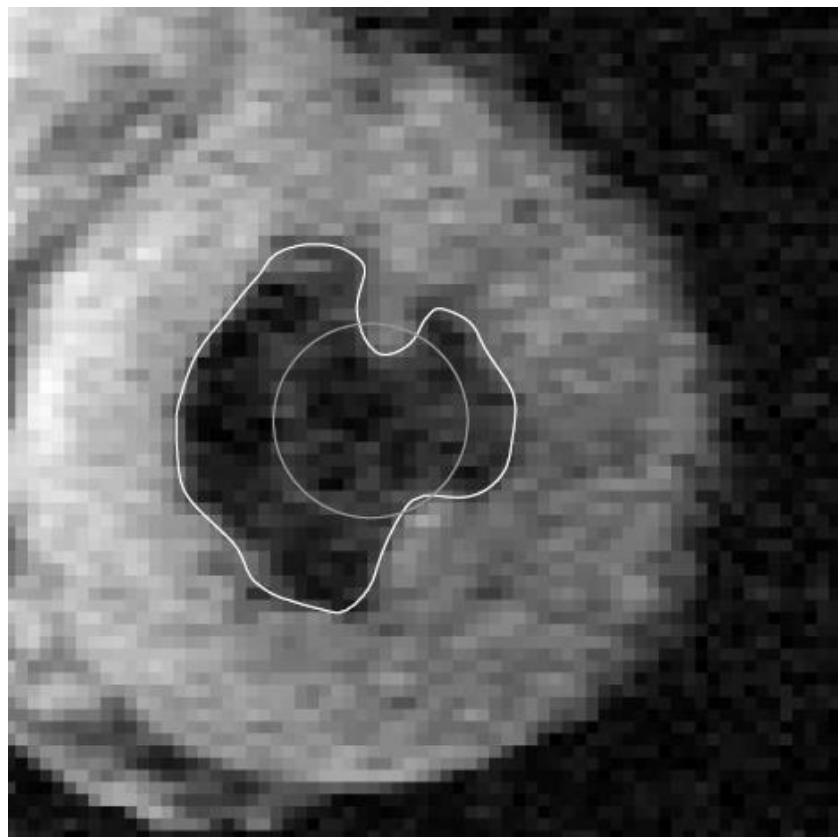
- › Deformable methods start with an initial contour placed in the image, either manually or automatically, which is then iteratively deformed, generating a new contour at each iteration.



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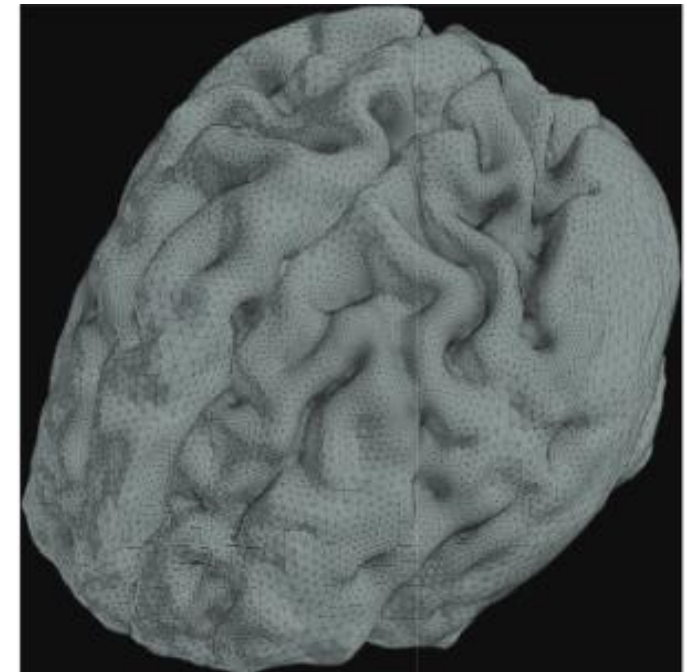
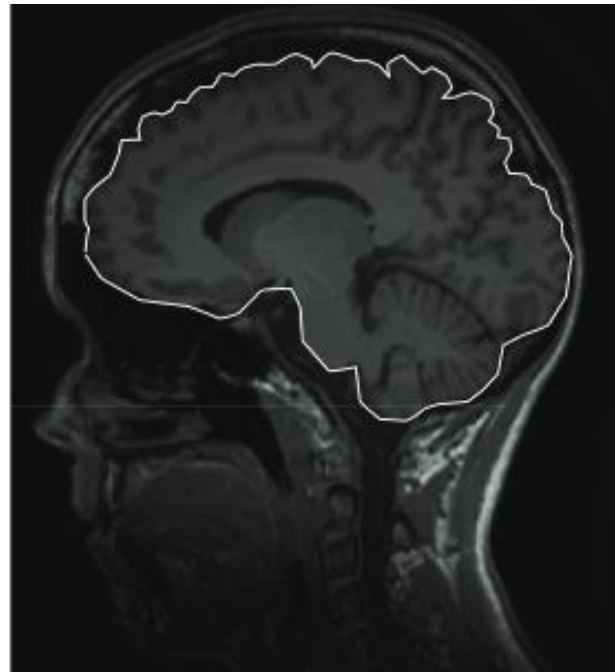
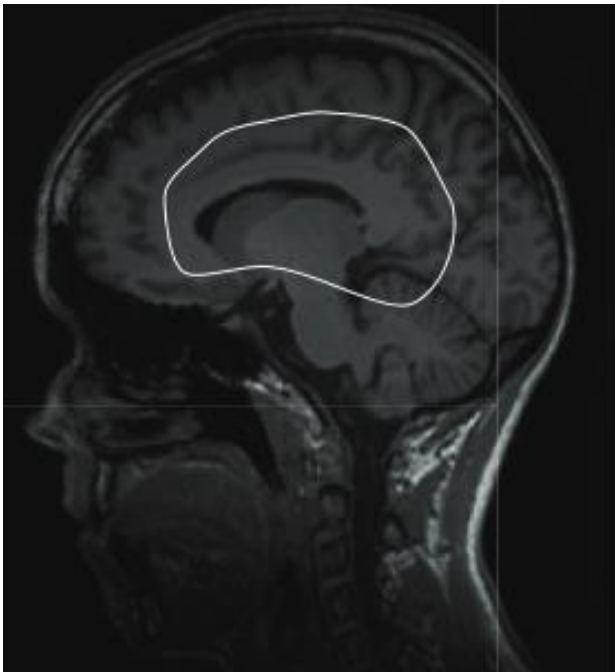
# Example (1)

› Heart chamber



## Example (2)

- › Initial condition (Left), Final result (Middle), and 3D example (Right)



# Approaches

- › Two main categories of deformable models:
  - Parametric (explicit) deformable model, Active Contour Models (ACM) or Snakes
  - Geometric (implicit) deformable model or level-set

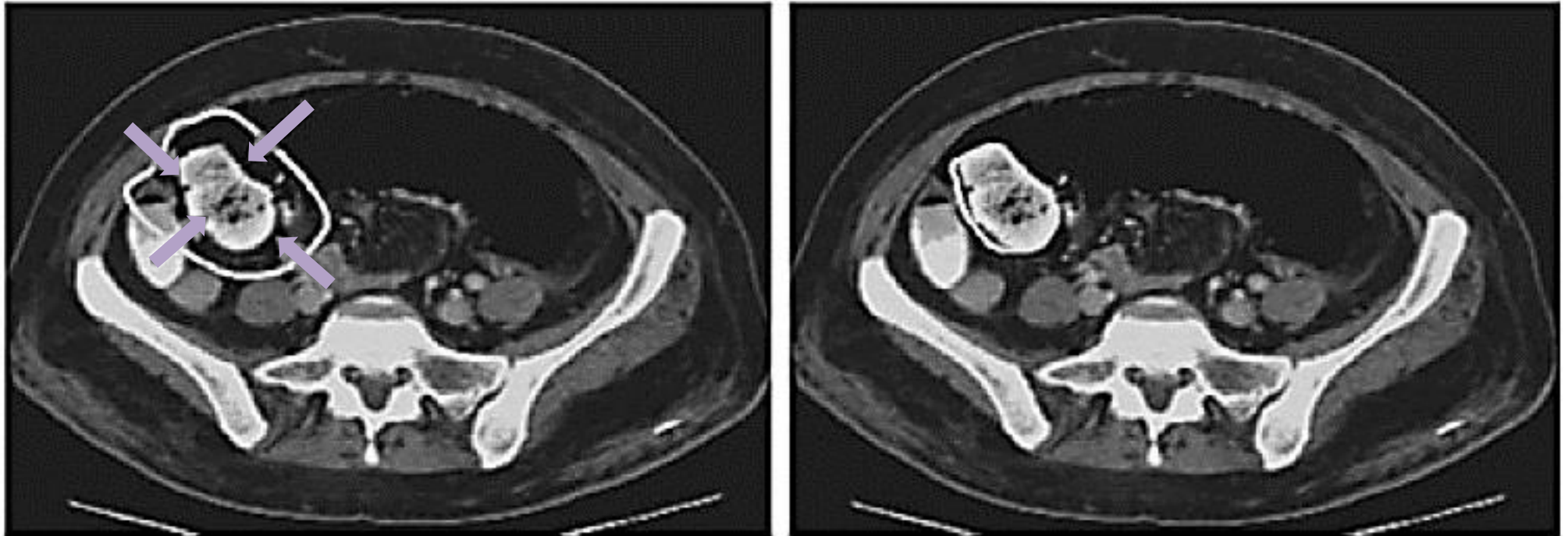
## Parametric Deformable Model

- › Track the boundary by matching the deformable model to the image curve, influenced by *external* and *internal* forces, in order to minimize the defined energy functional.
- › Internal force: include curve elasticity and rigidity and force resist deformation.
- › External force: Push the contour towards object true contours and forces resist deformation



# Parametric Deformable Model

› Example:

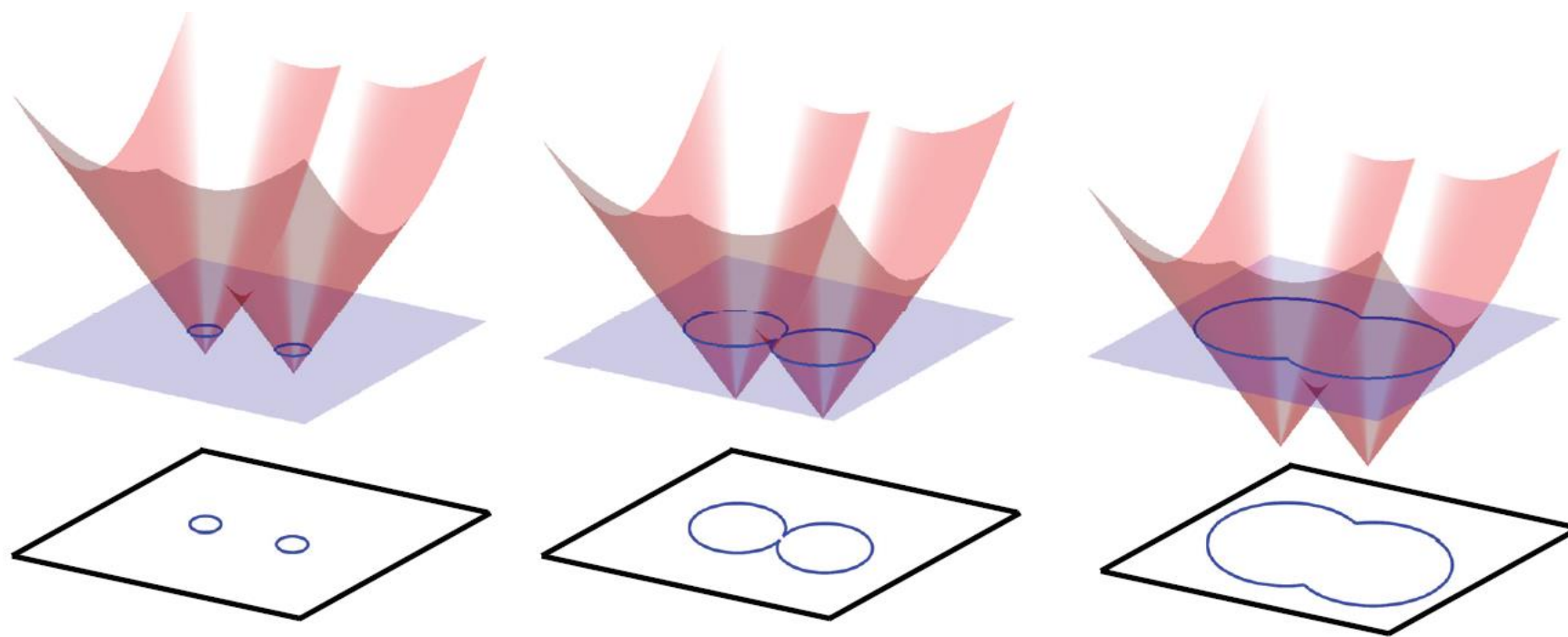


# Geometric Deformable Model

- › Using curve evolution theory and level set methods. Instead of parameterizing a curve, it is depicted as a zero level set of a higher dimensional function whose evolution defines the initial value problem.
- › Contour evolution is associated with **speed function** of level sets. Here, the contour is independent of the curves parameterization.

# Geometric Deformable Model

› Illustration:



# Parametric Deformable Model

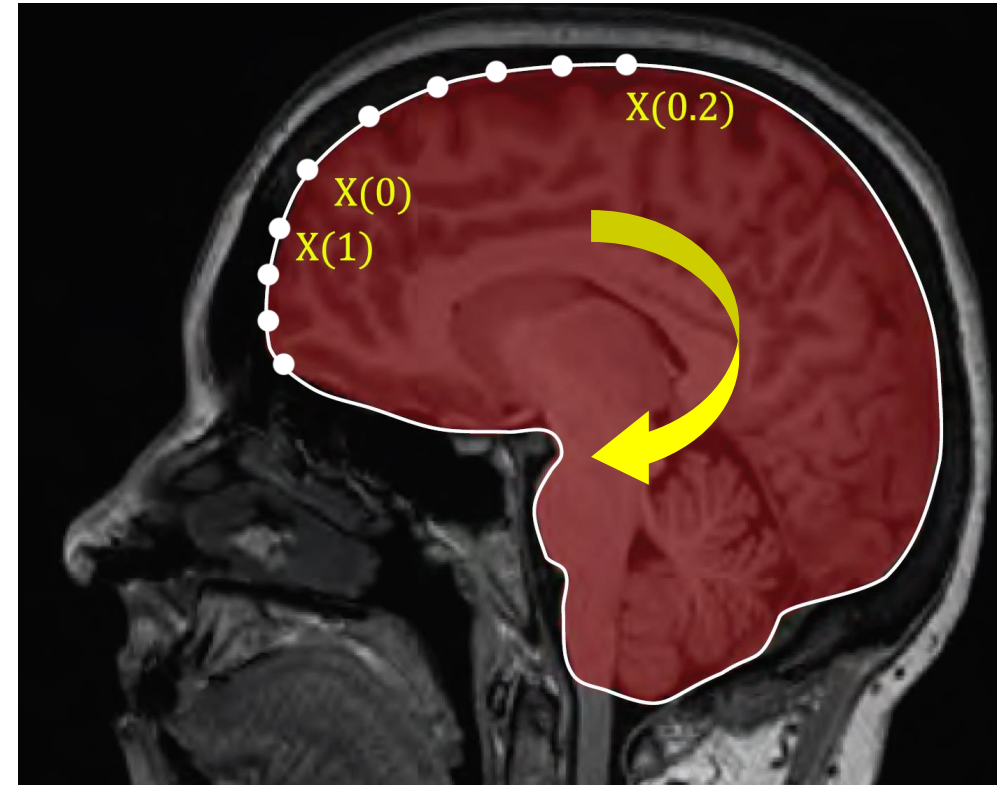
› Parametric Curve:

$$› X(s) = \begin{pmatrix} x(s) \\ y(s) \end{pmatrix}, \quad 0 \leq s \leq 1$$

› Example, circle:

$$-x(s) = r \cos(2\pi s)$$

$$-y(s) = r \sin(2\pi s)$$



# Elasticity Energy

› First derivative of curve is:

$$\frac{\partial X(s)}{\partial s} = X'(s) = \begin{pmatrix} x'(s) \\ y'(s) \end{pmatrix}$$

› Elasticity Energy is defined as:

$$\int_0^1 \left| \frac{\partial X(s)}{\partial s} \right|^2 ds$$

› Discrete Approximation:  $\left| \frac{\partial X(s)}{\partial s} \right|^2 \propto |X(s + \Delta s) - X(s)|^2$

› The distance between the successive points on the curve

# Rigidity/Bending Energy

› Second derivative of curve is:

$$\frac{\partial^2 X(s)}{\partial s^2} = X''(s) = \begin{pmatrix} x''(s) \\ y''(s) \end{pmatrix}$$

› Rigidity/Bending Energy or Stiffness is defined as:

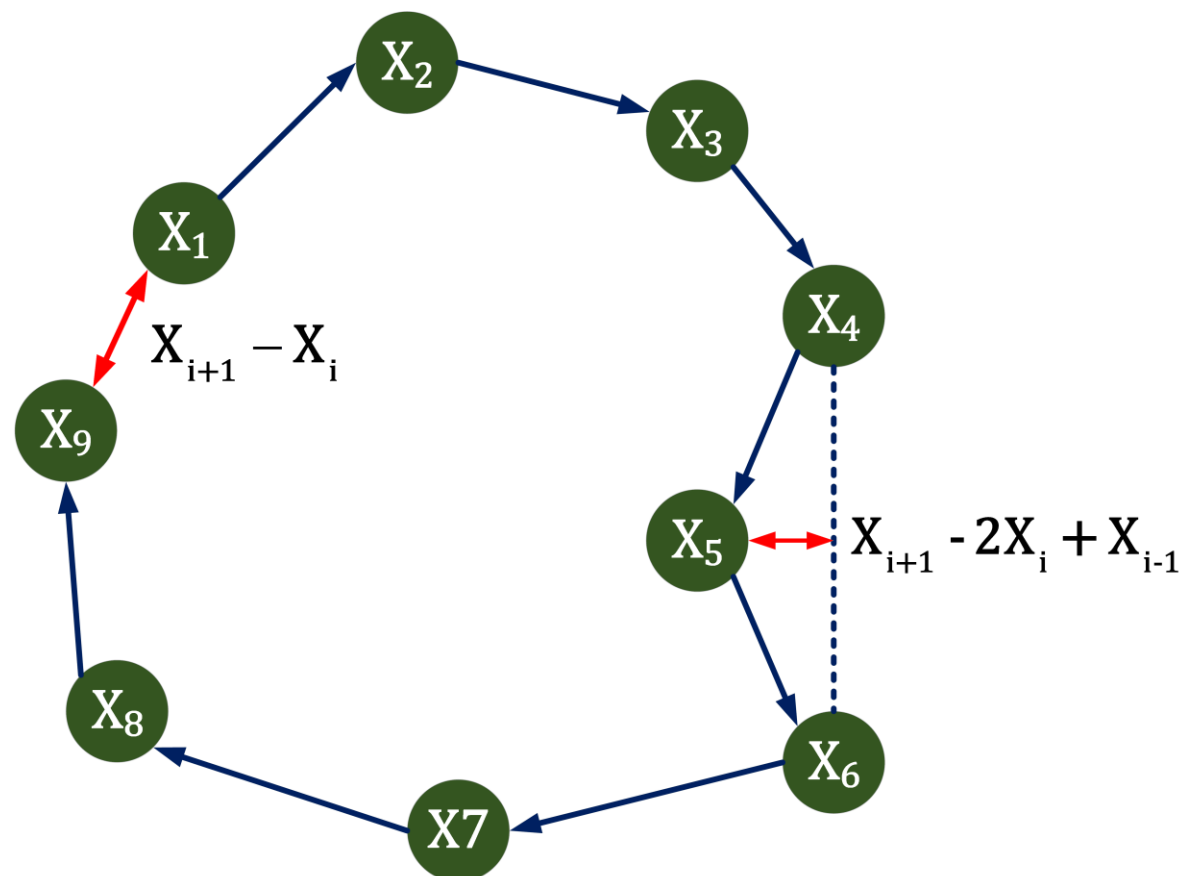
$$\int_0^1 \left| \frac{\partial^2 X(s)}{\partial s^2} \right|^2 ds$$

› Discrete Approximation:  $\left| \frac{\partial^2 X(s)}{\partial s^2} \right|^2 \propto |X(s + \Delta s) - 2X(s) + X(s - \Delta s)|^2$

› The deviation from straight line in three successive points

# Elasticity and Rigidity Illustration

› Elasticity and rigidity discrete illustration:



## Energy *minimization* formulation:

› A deformable contour is a curve,  $X(s) = (x(s), y(s))'$ ,  $0 \leq s \leq 1$  which moves through the spatial domain of an image to minimize the following energy functional:

$$\begin{aligned} \mathcal{E}(X) &= \frac{1}{2} \int_0^1 \{E_{internal}(X(s)) + E_{image}(X(s)) + E_{user}(X(s))\} ds \end{aligned}$$

$$\mathcal{E}(X) = \mathcal{E}_{internal}(X) + \underbrace{\mathcal{E}_{image}(X) + \mathcal{E}_{user}(X)}_{\mathcal{E}_{external}(X)}$$

› In what following we explain each term



## Internal (Contour) energy - Elasticity:

- › Internal (Contour) energy:

$$E_{internal}(X(s)) = \alpha(s)E_{Elasticity}(X(s)) + \beta(s)E_{Rigidity}(X(s))$$

$$E_{internal}(X(s)) = \alpha(s) \left| \frac{\partial X(s)}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 X(s)}{\partial s^2} \right|^2$$

- › The elasticity term discourages stretching and makes the model behave like an *elastic string*.
- › Decreasing elasticity allows the contour to increase in length, while increasing elasticity increases the tension of the model by reducing its length.

## Internal (Contour) energy - Rigidity:

- › Internal (Contour) energy:

$$E_{internal}(X(s)) = \alpha(s)E_{Elasticity}(X(s)) + \beta(s)E_{Rigidity}(X(s))$$

$$E_{internal}(X(s)) = \alpha(s) \left| \frac{\partial X(s)}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 X(s)}{\partial s^2} \right|^2$$

- › The rigidity term discourages bending and makes the model behave like a *rigid rod*.
- › Decreasing rigidity allows the active contour model to develop corners, while increasing rigidity makes the model smoother and less flexible.

## External (image and user) energy:

- › External (image and user) energy:

$$E_{external}(X(s)) = E_{image}(X(s)) + E_{user}(X(s))$$

- › There are many choices for  $E_{image}(X(s))$  and  $E_{user}(X(s))$
- › A typical potential energy function designed to lead a deformable contour toward step edges is:

$$E_{image}(X(s)) = -w_e |\nabla [G_\sigma(x, y) * I(x, y)]|^2$$

- › We will discuss more about this.

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# This energy minimization problem

› This energy minimization problem:

$$\mathcal{E}(X) = \frac{1}{2} \int_0^1 \left\{ \alpha(s) \left| \frac{\partial X(s)}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 X(s)}{\partial s^2} \right|^2 + E_{external}(X(s)) \right\} ds$$

› may be solved by calculus of variation:

$$\frac{\partial}{\partial s} \left( \alpha(s) \frac{\partial X(s)}{\partial s} \right) - \frac{\partial^2}{\partial s^2} \left( \beta(s) \frac{\partial^2 X(s)}{\partial s^2} \right) - \nabla \left( E_{external}(X(s)) \right) = 0$$

› To gain some insight about the physical behavior of deformable contours

$$F_{internal}(X) + F_{external}(X) = 0$$

# How to solve Euler-Lagrange equation?

- › The deformable contour is made dynamic by treating  $X(s)$  as a function of  $t$  as well as  $s$ ,  $X(s, t)$

$$\lambda \frac{\partial X}{\partial t} = \frac{\partial}{\partial s} \left( \alpha \frac{\partial X}{\partial s} \right) - \frac{\partial^2}{\partial s^2} \left( \beta \frac{\partial^2 X}{\partial s^2} \right) - \nabla E_{external}(X)$$

$$\lambda \frac{\partial X}{\partial t} = F_{internal}(X) + F_{external}(X) = F_{total}(X)$$

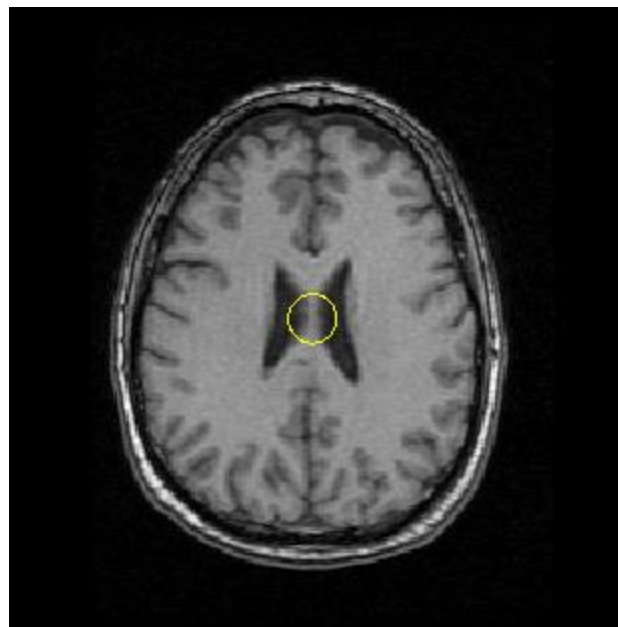
- › Steady state solution of above equation is solution of static equation

$$X(s, t + \Delta t) = X(s, t) + \frac{\Delta t}{\lambda} F_{total}(X(s, t)), \quad X(s, 0) = X_0(s)$$

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# Illustration

› How it works:



## General Formulation

- › Directly force formulation permits the use of more general types of external forces that are not potential forces, i.e., *forces that cannot be written as the negative gradient of potential energy functions*, using Newton's 2<sup>nd</sup> law:

$$\mu \frac{\partial^2 X}{\partial t^2} + \lambda \frac{\partial X}{\partial t} - \frac{\partial}{\partial s} \left( \alpha \frac{\partial X}{\partial s} \right) + \frac{\partial^2}{\partial s^2} \left( \beta \frac{\partial^2 X}{\partial s^2} \right) = -\nabla E_{external}(X)$$

- › In image segmentation applications we set  $\mu$  equal to zero, hence:

$$\lambda \frac{\partial X}{\partial t} = F_{internal}(X) + F_{external}(X), \quad F_{external}(X) = \sum_{i=1}^N F_N(X)$$

# Multiscale Gaussian potential force (image)

## › Definition:

$$E_{image}(X(s)) = -w_e |\nabla[G_\sigma(x, y) * I(x, y)]|^2, w_e > 0$$

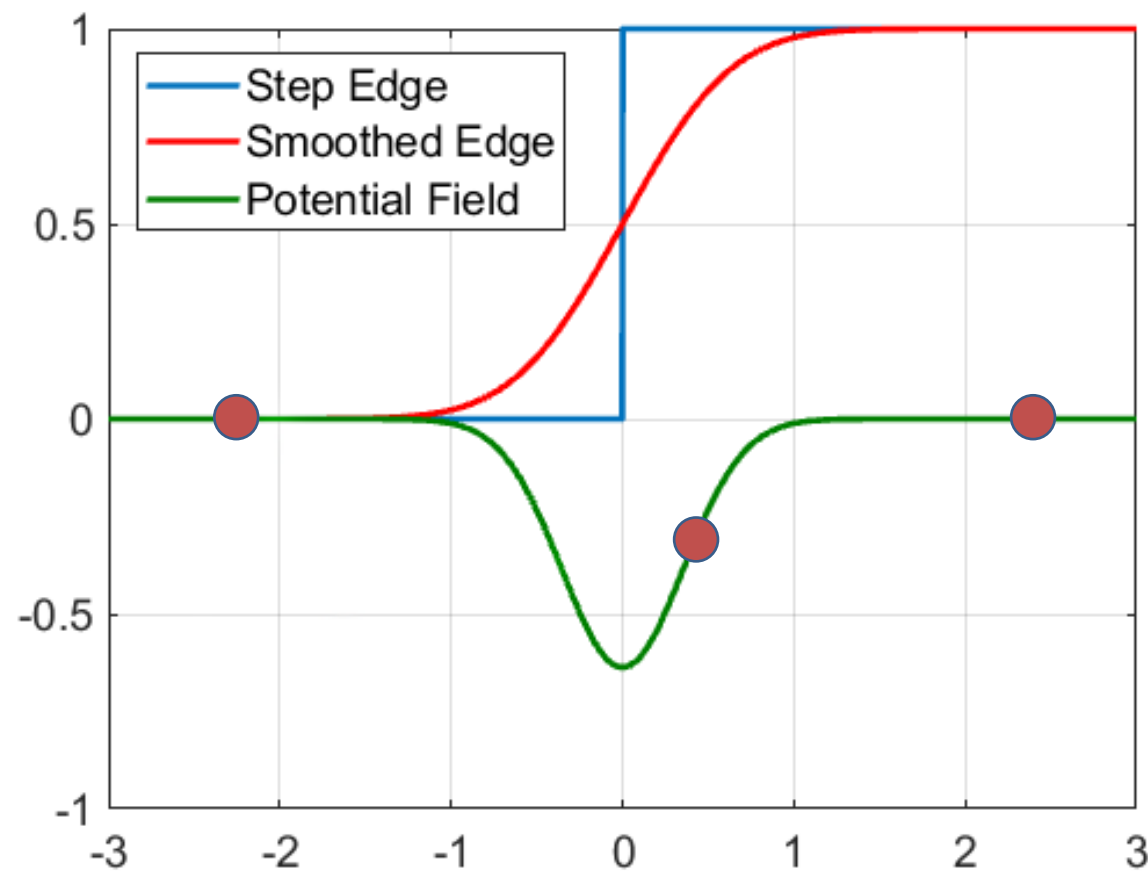
- › Which designed to lead a deformable contour toward step edges.
- › Effect of  $G_\sigma(x, y)$ :
  - Noise reduction
  - Broaden potential wall



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# Multiscale Gaussian potential force (image)

› Multiscale Gaussian potential force:



# Multiscale Gaussian potential force (image)

- › How to select Gaussian filter parameter ( $\sigma$ ):
- › Small  $\sigma$ :
  - Proc: Follow the boundary accurately,
  - Cons: Gaussian potential force can only attract the model toward the boundary when it is initialized *nearby*.
- › Large  $\sigma$ :
  - Proc: Broaden attraction rang
  - Cons: Steady state solution will be far from true edge point
- › Trade off strategy:
  - Multiscale (coarse-to-fine), monotonically decreasing  $\sigma(t)$

## Pressure force or Balloon force (user):

› Definition:

$$F_{Balloon}(X(s)) = k \frac{\vec{N}(X)}{|\vec{N}(X)|}$$

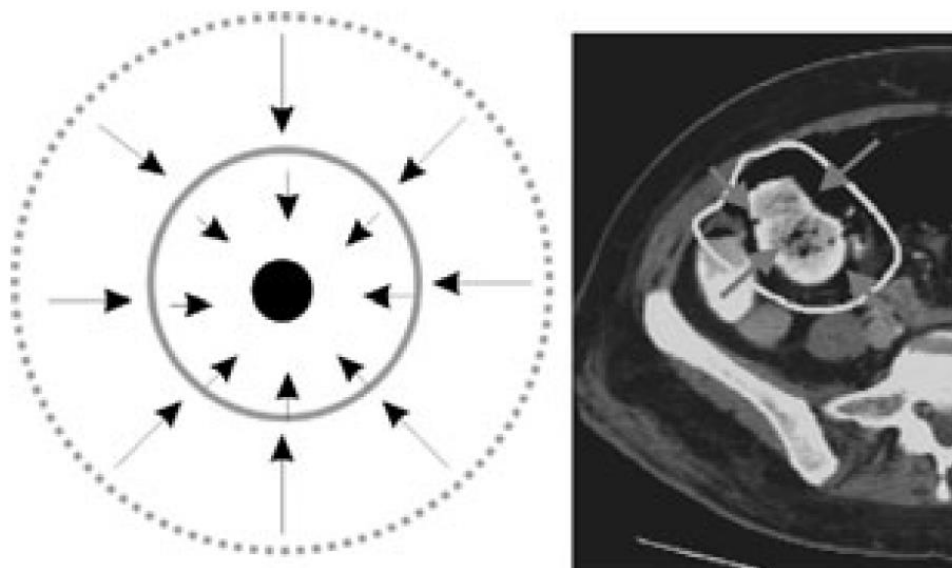
- › Where  $\vec{N}(X)$  is inward normal vector and sign of  $k$  determine whether to inflate or deflate the model and is typically chosen by the user.
- › The value of  $k$  determines the strength of the pressure force. It must be carefully selected so that the pressure force is *slightly smaller* than the Gaussian potential force at *significant* edges, but *large* enough to pass through *weak* or spurious edges.

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# Pressure force or Balloon force (user):

› Illustration:

$$F_{Balloon}(X(s)) = k \frac{\vec{N}(X)}{|\vec{N}(X)|}$$



## Distance potential force (image):

- › We assume a prior knowledge about good local edge points
- › We construct a distance map,  $d(x, y)$ , at each pixel obtained by calculating the distance between the pixel  $(x(s), y(s))$  and the closest boundary point (prior knowledge), based on any distance function:

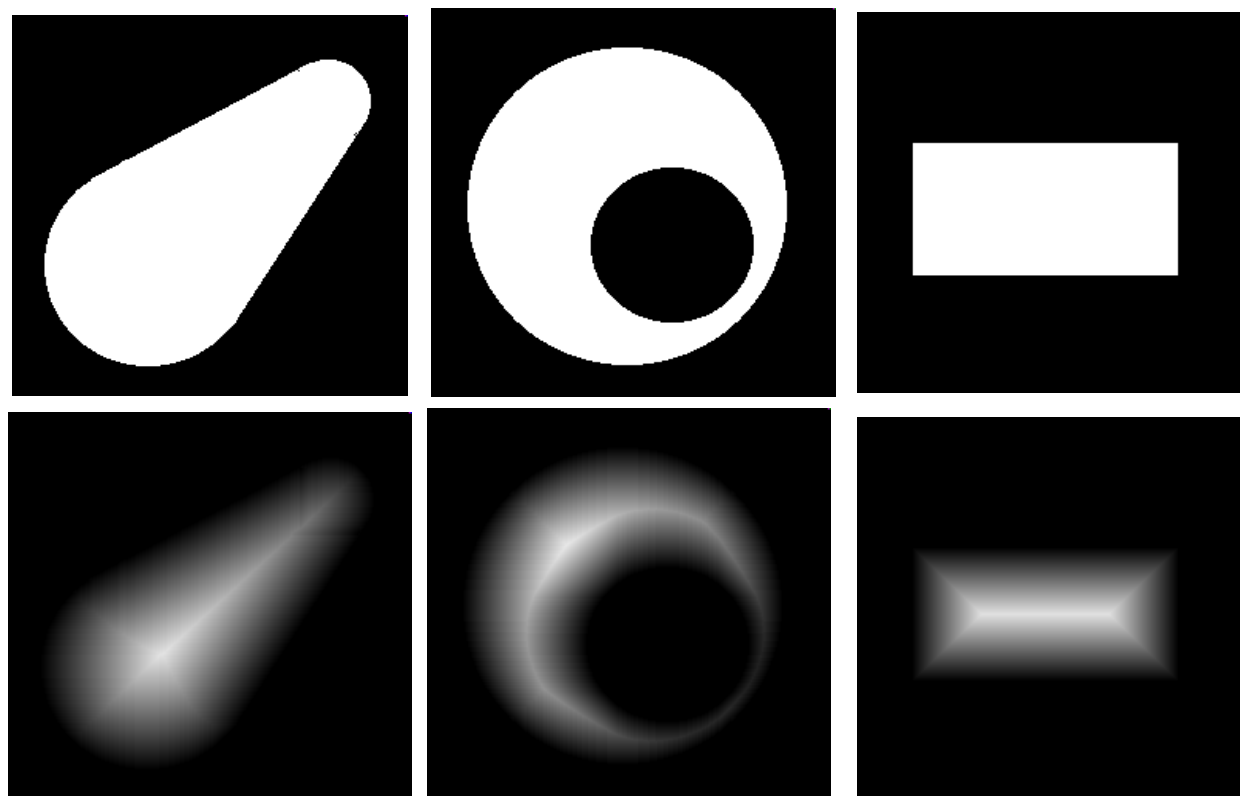
$$E_{distance}(x, y) = -w_d \exp(-d(x, y))$$

$$E_{distance}(x, y) = -\frac{1}{\max(d(x, y), 1)}$$

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# Distance potential force (image):

› Distance map:



## Dynamic Distance Force (image):

- › We assume a prior knowledge about good local edge points
- › We construct a *signed* distance map,  $D(x, y)$ , at each pixel obtained by calculating the distance between the pixel  $(x(s), y(s))$  and the closest boundary point (prior knowledge), based on any distance:

$$F_D(x, y) = w_D \frac{D(x, y)}{D_{max}} \vec{N}(X)$$

# The End

› AnY QuEsTiOn?

