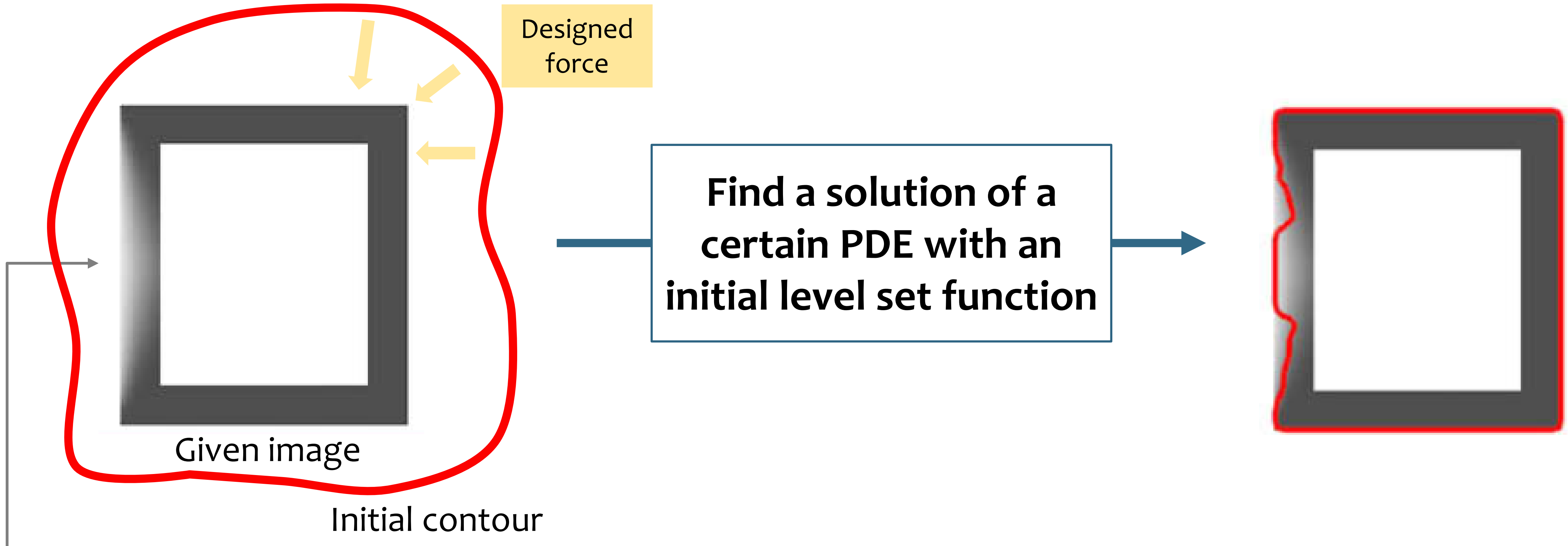
Research Areas

- Mathematical Image Processing
  - Weak edge detection & segmentation
  - Semiconductor defect inspection
- Industrial CT Imaging
  - X-ray CT artifact reduction (Beam hardening, Scattering)
- Algorithms for parallel computing
  - Domain decomposition methods for mathematical optimization
  - Isogeometric analysis: dynamic cloth simulation
  - Parallel deep neural networks

Weak Edge detection & Segmentation

Active contour for image segmentation



Weak edge

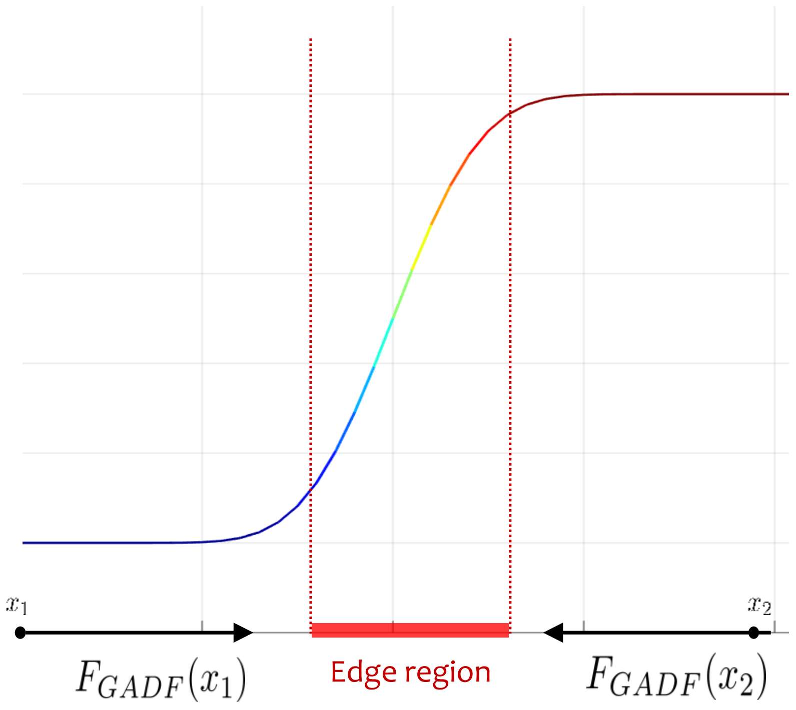
Region-Aided Geometric Snake, X. Xie and M. Mirmehdi (2004)

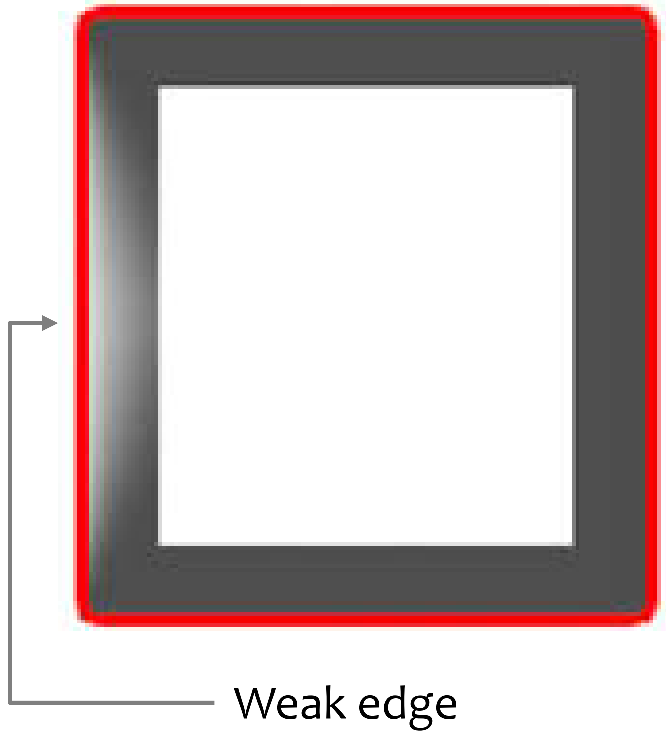
Drawback : Leakage at weak edges

Weak Edge detection & Segmentation

Edge region from Geometric attraction-driven flow (GADF)

$$F_{GADF}(\mathbf{x}) = sgn\left(\frac{d^2}{dt^2} I(\mathbf{x} + t\nabla I)\Big|_{t=0}\right)\frac{\nabla I}{\|\nabla I\|}$$

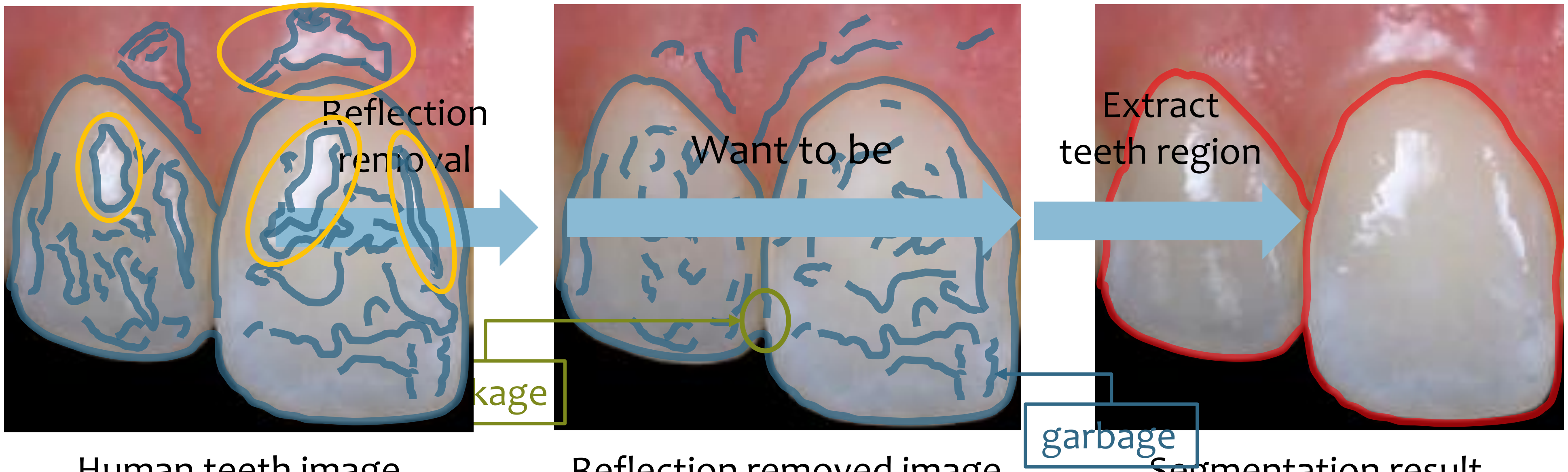




[Geometric attraction-driven flow for image segmentation and boundary detection, J. Hahn, C.-O. Lee (2010)]

Weak Edge detection & Segmentation

Human teeth region segmentation with reflection removal



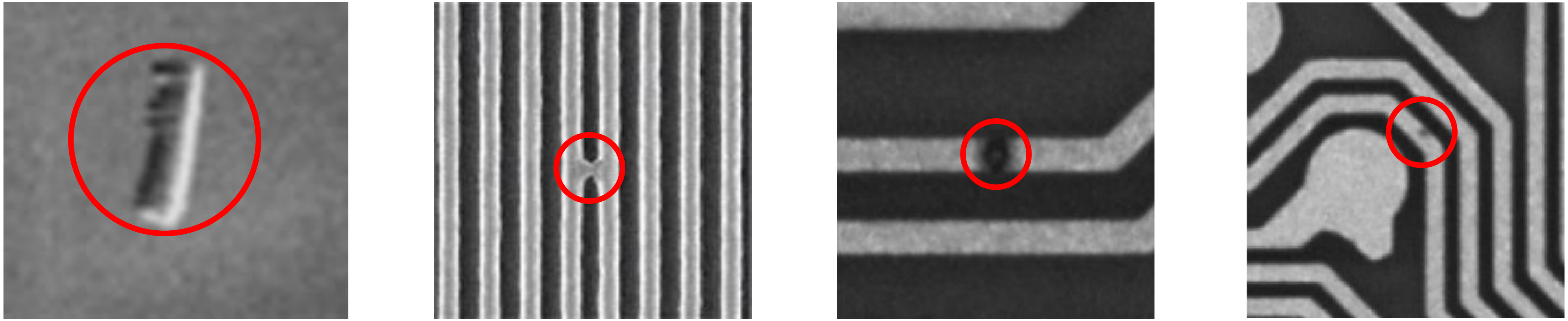
Human teeth image and edge regions (GADF) | Reflection removed image | Segmentation result

Problems

Large edge regions forming closed regions
make it difficult to extract teeth regions

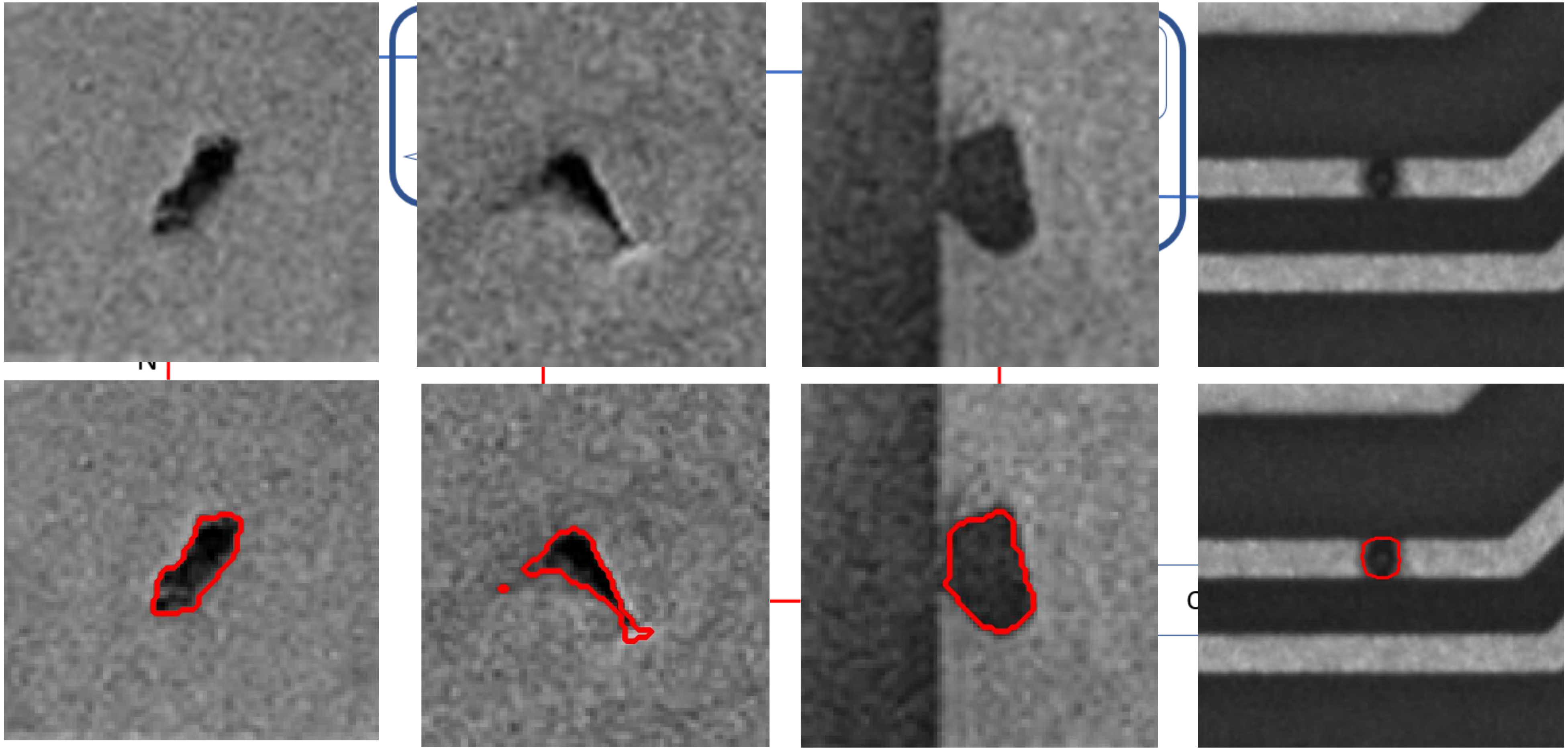
Semiconductor defect inspection

Defects on semiconductor



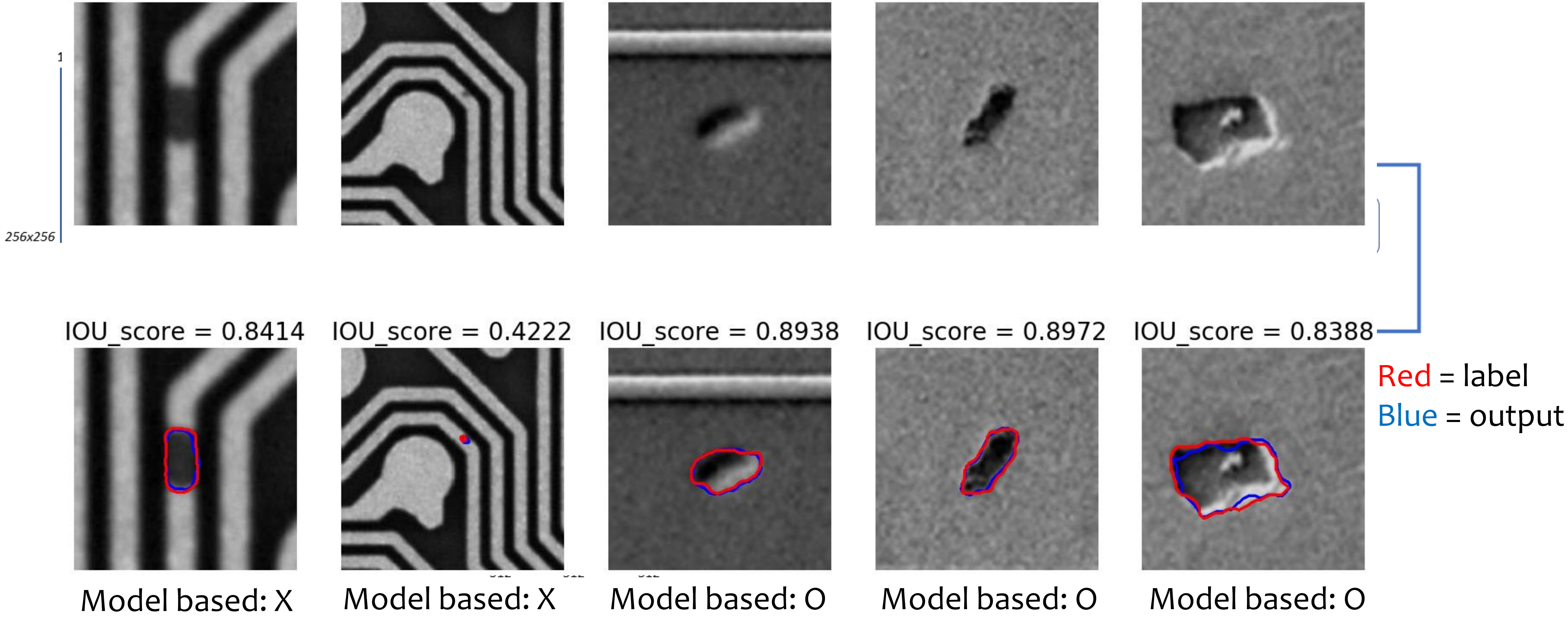
Semiconductor defect inspection

Algorithm result



Semiconductor defect inspection

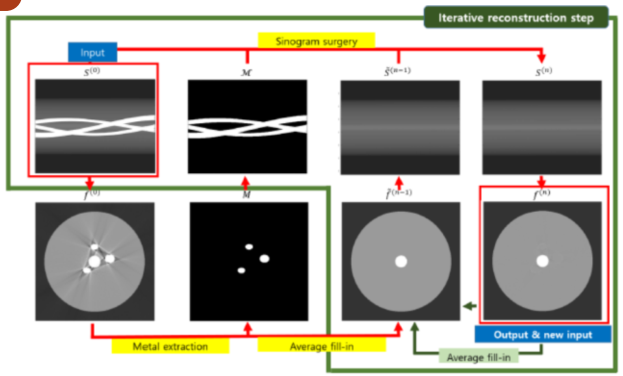
Machine learning result



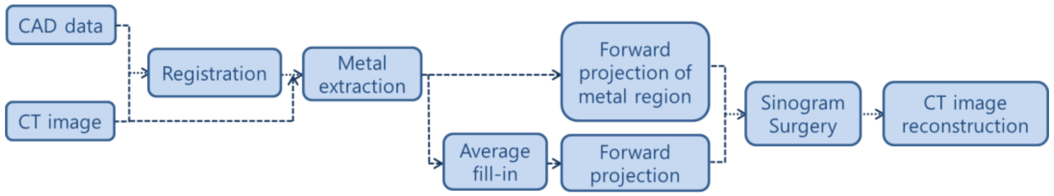
Artifact reduction in X-ray CT

Beam hardening reduction

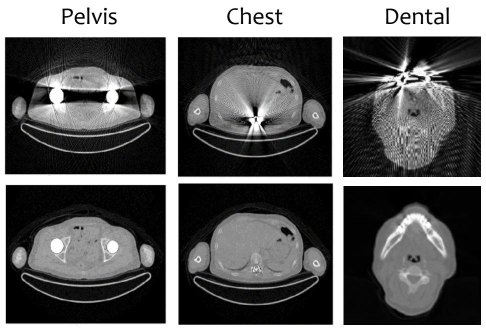
2-D Algorithm



3-D Algorithm for Industrial CT



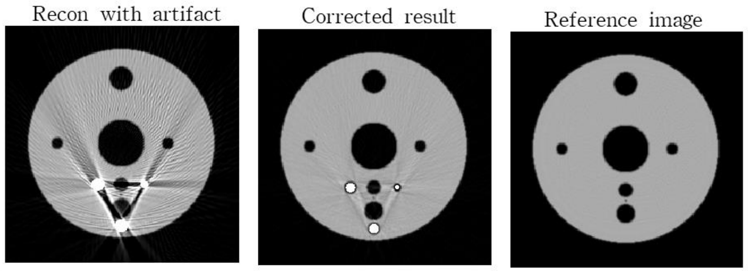
Application I. Clinical CT



Segmentation issues
- for the case of complex structures
- with other physical artifacts such as scattering

Application II. Industrial conebeam CT: flaw detection

- Utilizing CAD data for shape prior information



In-line inspection system: real-time
geometry management
Image quality control: from data acquisition to image reconstruction

Artifact reduction in X-ray CT

Scattering reduction

Minimization problem $\arg\min_{(A,\alpha,\beta,\sigma_1,\sigma_2,B)} \|I - (I_p + I_s(A,\alpha,\beta,\sigma_1,\sigma_2,B))\|$

for scattering kernel

$$I_s(x,y) = (I_p(x,y)A_f(x,y)) * h_s(x,y)$$

where

$$A_f = A \cdot \left(\frac{I_p(x,y)}{I_0(x,y)}\right)^\alpha \cdot \left(\ln\left(\frac{I_0(x,y)}{I_p(x,y)}\right)\right)^\beta$$

$$h_s = \left[\exp\left(\frac{-r^2}{2\sigma_1^2}\right) + B\exp\left(\frac{-r^2}{2\sigma_2^2}\right)\right]$$

Improved scatter correction using adaptive scatter kernel superposition, M.Sun & J.M. Star-Lack (2010)

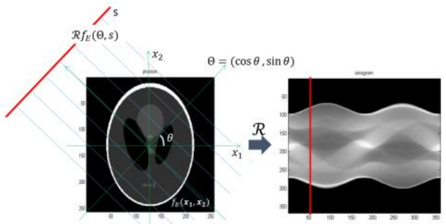
Highly non-linear problem

Solve the non-linearity by adopting **proper constraint** such as **range theorem**, so called **consistency condition** of X-ray projection data

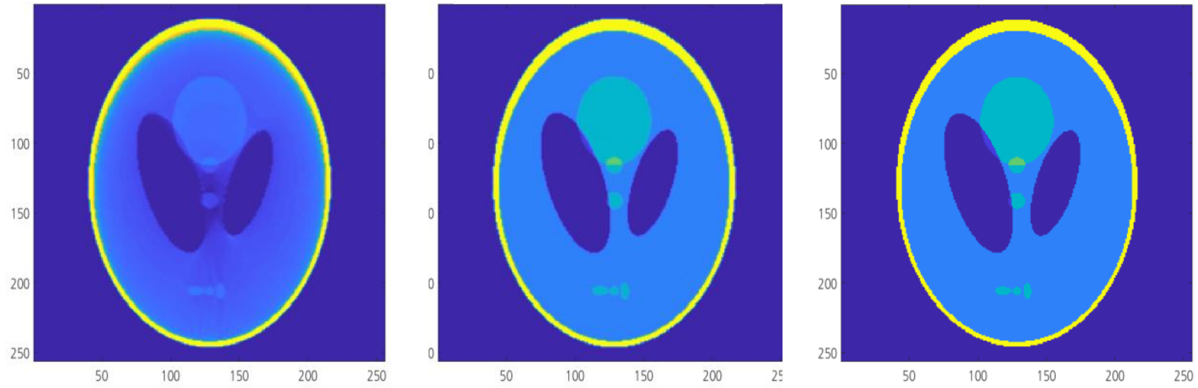
0-th Consistency condition

$$\int f(x,y)\,dx\,dy = \int \text{Sinogram}(\theta,l)\;dl \;\text{ for all } \theta$$

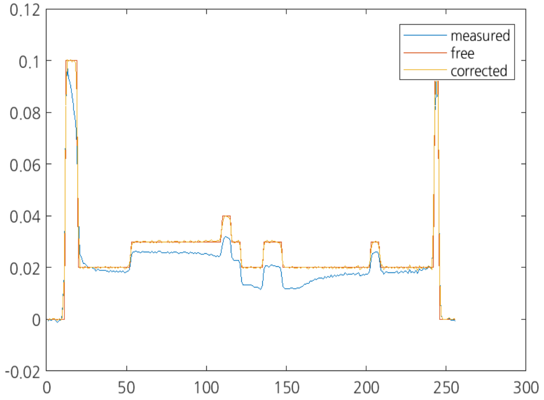
where $f(x,y)$ is a CT image



Scattered image | Corrected image | Reference image



Profile of center slices



$$I_p \approx I_0 \exp(-\mathcal{R}f_{\text{CAD}})$$

Find $(A, \alpha, \beta, \sigma_1, \sigma_2, B)$

Proposed method results:
(0.0004005, -0.30085, 1.4969, 21.99, 5.0046, 2.3576)
Reference parameter values:
(0.0004, -0.3, 1.5, 22, 5, 2.36)
Relative error: 0.0040786 (0.41%)

Domain Decomposition Methods for Mathematical Optimization

Mathematical optimization

- Partial differential equations

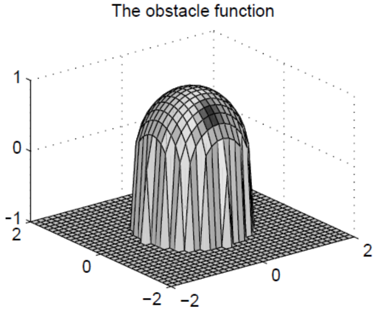
  - Elliptic BVPs and Lax-Milgram theorem

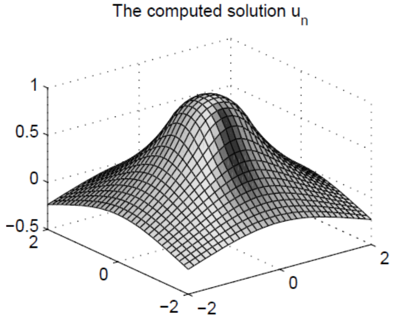
$$\begin{cases} -\Delta u = f & \text{in } \Omega \\ u = 0 & \text{on } \partial\Omega \end{cases} \Leftrightarrow \min_{u \in H_0^1(\Omega)} \frac{1}{2} \int_\Omega |\nabla u|^2 \, dx - \int_\Omega f u \, dx$$

- Computational mechanics

  - Obstacle problem

$$\min_{u \in K} F(u) \qquad K = \{u \in V : u \geq \psi \text{ in } \Omega\}$$





- Image processing

  - Euler's elastica image inpainting

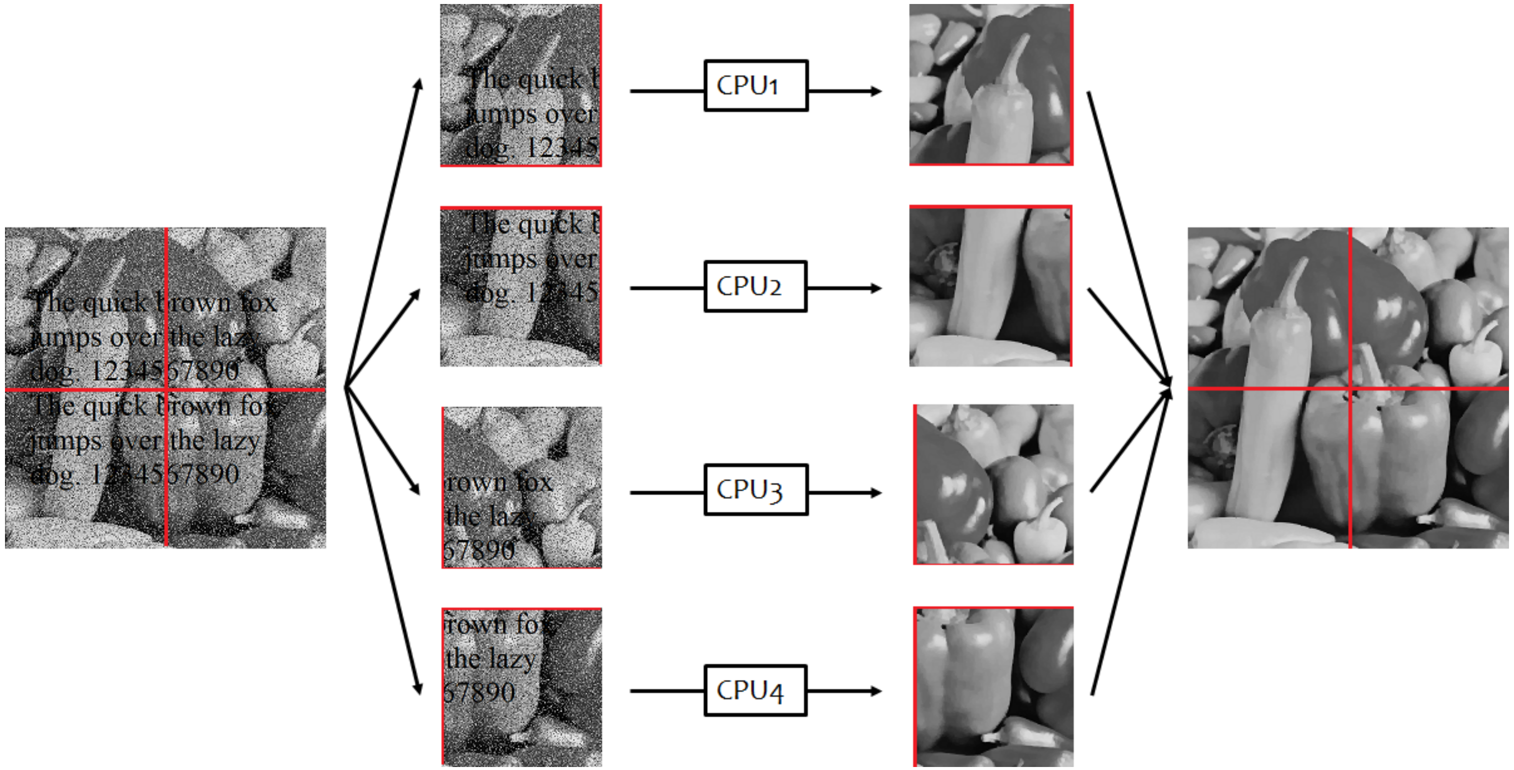
$$\min_{u \in V} \frac{\alpha}{2} \|Au - f\|_2^2 + \int_\Omega \left[a + b \left(\nabla \cdot \frac{\nabla u}{|\nabla u|} \right)^2 \right] |\nabla u| \, dx$$

(a) 80% missing pixels (b) PSNR: 28.59

Domain Decomposition Methods for Mathematical Optimization

Domain decomposition methods

- Parallel solvers suitable for distributed systems
- Local problems in subdomains are solved in parallel.



Domain Decomposition Methods for Mathematical Optimization

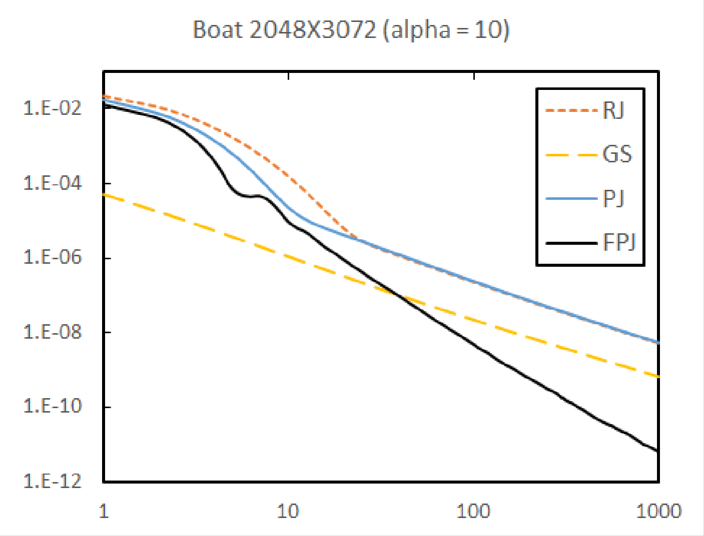
Challenging issues

- How to deal with nonsmooth/nonconvex terms in the energy functional?

$$\min_{u \in V} \frac{\alpha}{2} \|Au - f\|_2^2 + \underline{\int_\Omega \left[a + b \left(\nabla \cdot \frac{\nabla u}{|\nabla u|} \right)^2 \right] |\nabla u| \, dx}$$

nonsmooth/nonconvex

- How to ensure the convergence of the algorithm mathematically?
- How to improve the performance of the algorithm?



C.-O. Lee and J. Park (SIIMS 2019)
- Convergence rates of the energy functional differ algorithm by algorithm.

Dynamic cloth simulation

Tool : Isogeometric analysis (IGA)

* NURBS: CAD geometry basis = FE analysis basis

Cloth simulation : R. Bridson, S. Marino, R. Fedkiw (2003)

Kirchhoff-Love shell + IGA : J.Kiendl (2009)

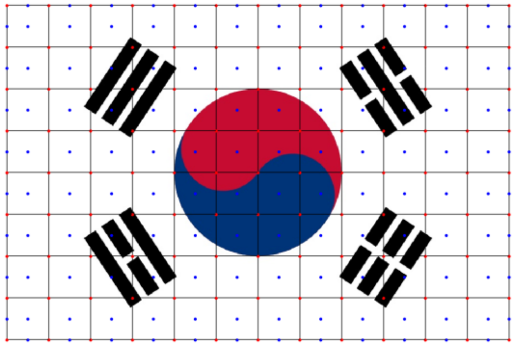
IGA with trimmed surfaces : HJ Kim, YD Seo, SK Youn (2010)

Kirchhoff-Love shell + IGA + Cloth simulation : J. Lu, C. Zheng (2014)

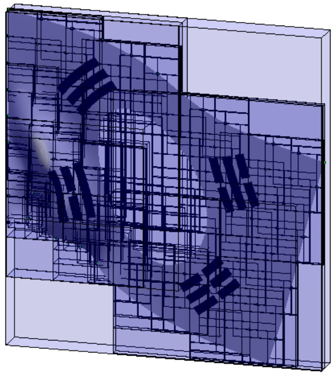
Kirchhoff-Love element : displacement-based; no rotational dofs are needed.
IGA : short modeling time, maintains higher order continuity.

Algorithm of dynamic cloth simulation

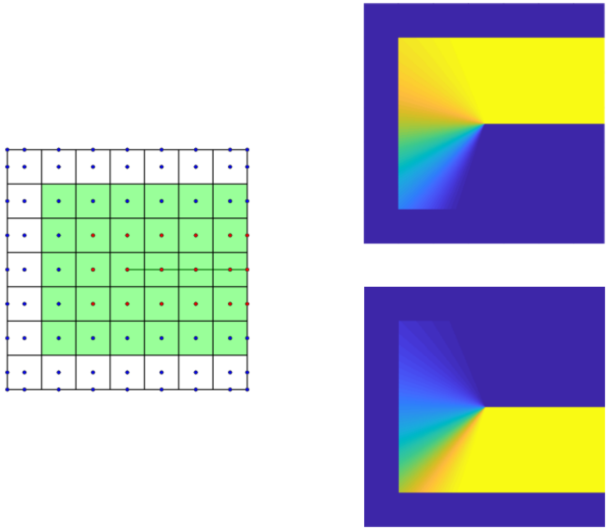
1. Predict positions of control points at t^{n+1}
2. Update contact test points and AABB tree structure of surfaces
3. Find contact candidates and calculate contact response
4. Projecting velocity of physical points to control points
5. Determine the position of control points at t^{n+1}
6. Calculate stiffness and decide velocity and acceleration by dynamic equilibrium



Contact test points and control points

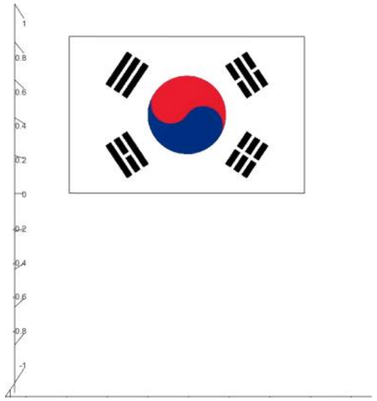


AABB(Axis Aligned Bounding Box) tree



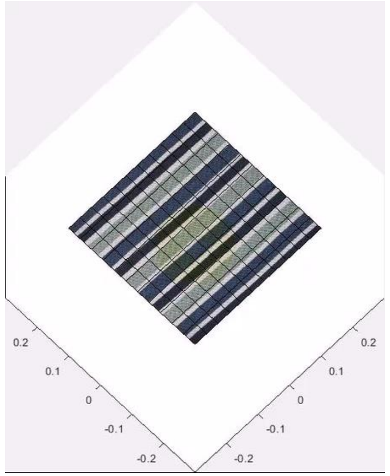
split function (yellow=1 , blue=0)
in the parameter space

Results of cloth simulation

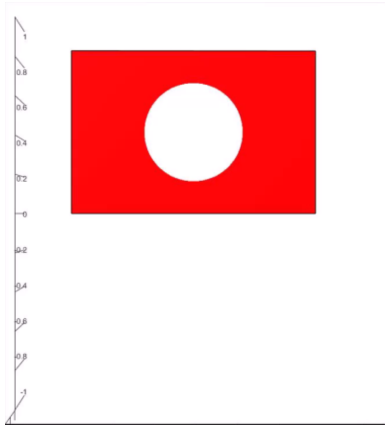


1. Flag draping

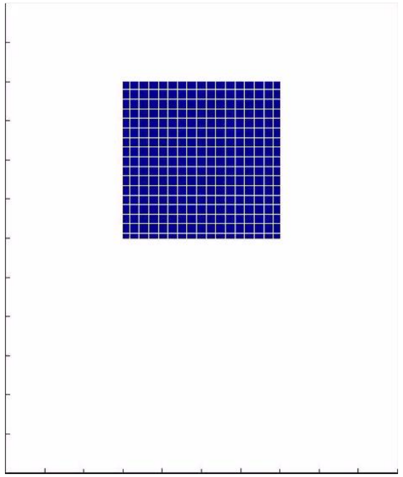
3. Cutted cloth



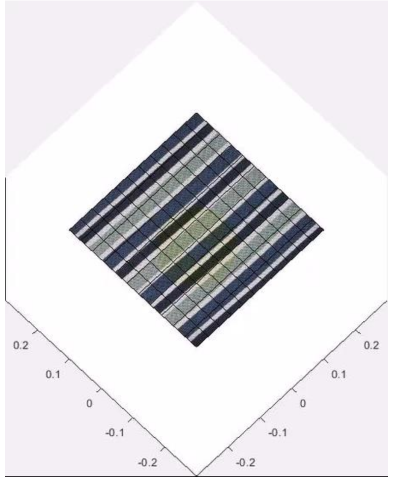
5. Cloth draping over sphere



2. Trimmed flag draping



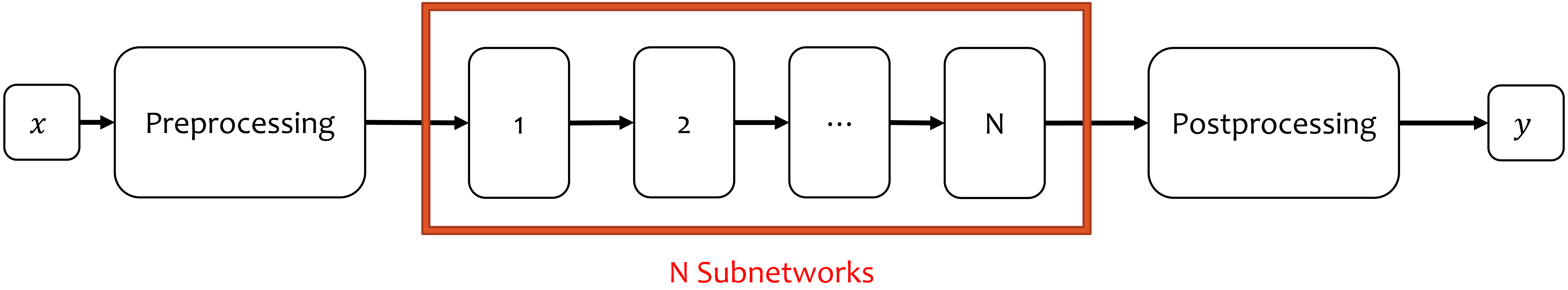
4. Cutting cloth with initial crack



6. Cloth draping over sphere with splitting function

Parallel deep neural network

Typical deep neural network (Feed forward neural network)



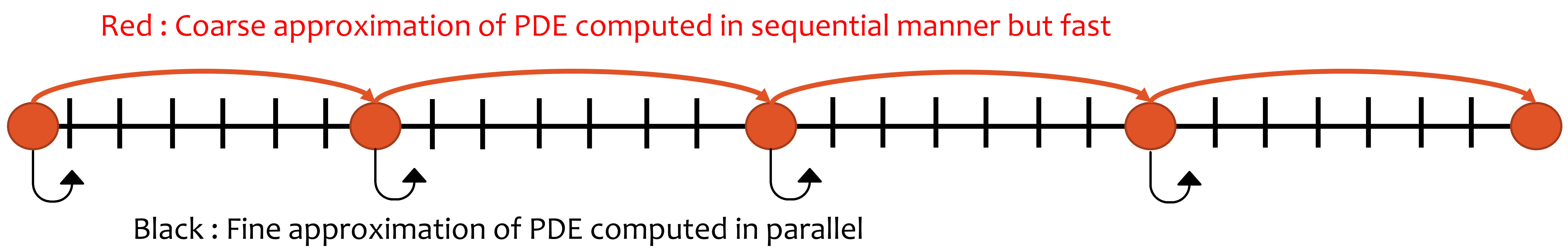
Parallel deep neural network

Problems

- As the depth of network becomes deeper, its training time becomes longer.
- How to accelerate DNN training using multiple GPUs?

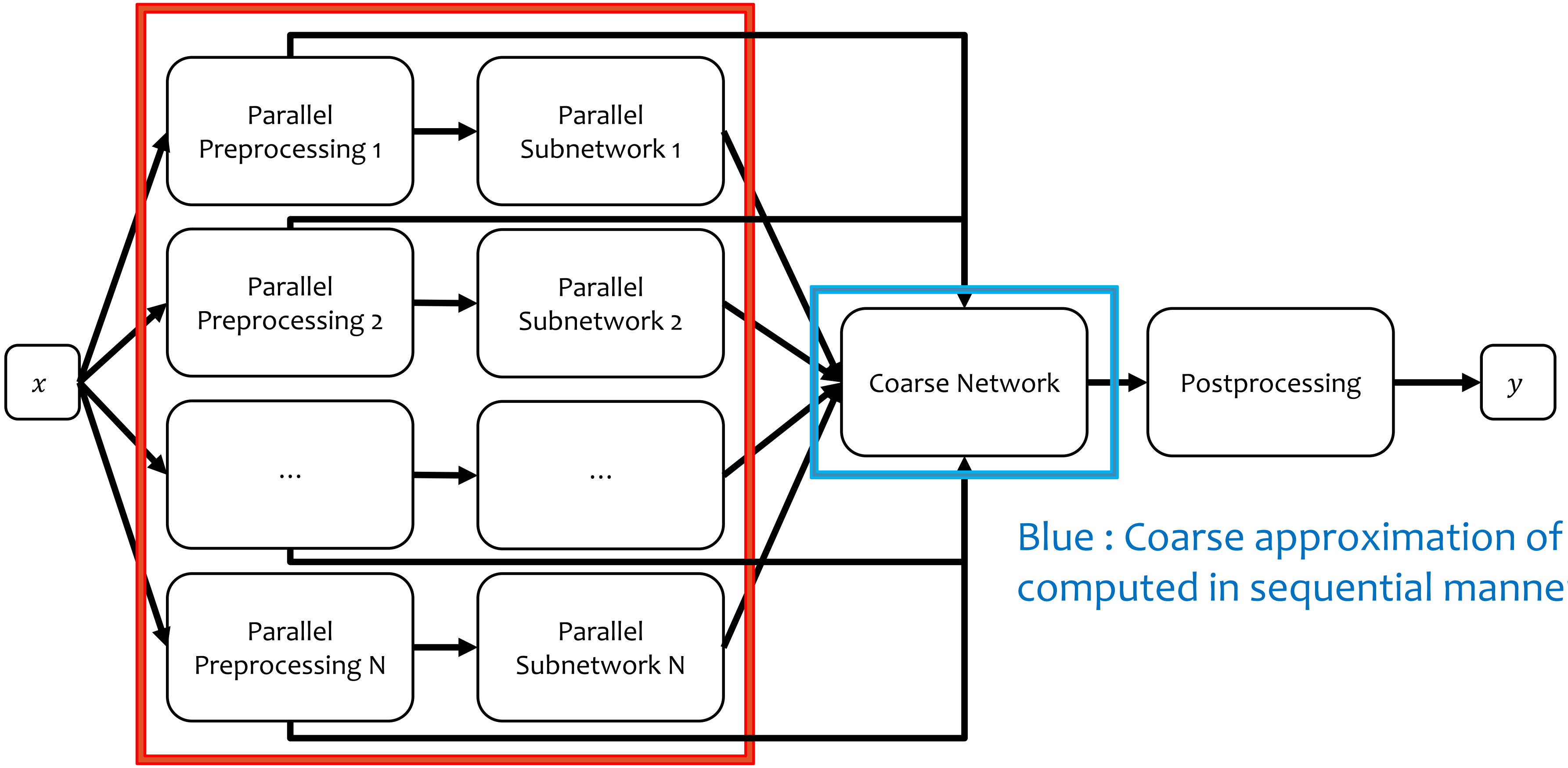
Motivation

- Lions et al. (2001) – A "parareal" in time discretization of PDE's



Parallel deep neural network

Parareal neural network



Blue : Coarse approximation of subnetworks computed in sequential manner but fast

Red : Preprocessing and subnetworks computed in parallel