

Digital Curvature Evolution Model for Image Segmentation

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Discrete Geometry for Computery Imagery

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Presentation plan

Introduction

- Motivation problems
- Regularization in imaging
- Curvature as regularization
- Discretization and multigrid convergence

Contribution

- Curve Evolution Model
- Interpretation
- Discussion and application

Conclusion

Image segmentation

Image segmentation

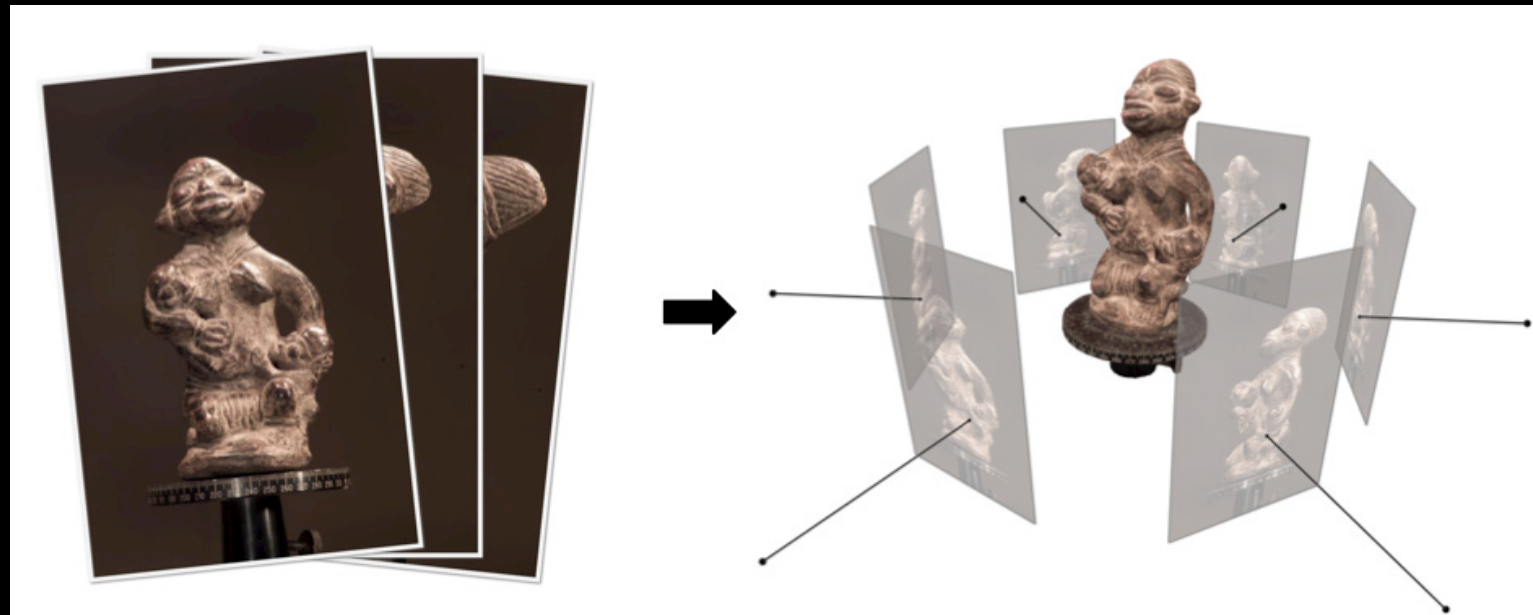


Denoising



[Unger, Werlberger, 2011]

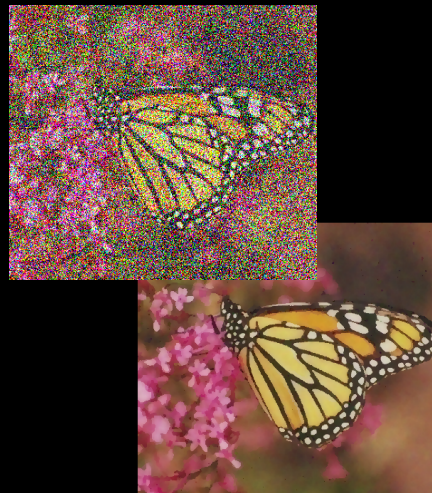
3D Reconstruction



[Furukawa, Hernández 2015]



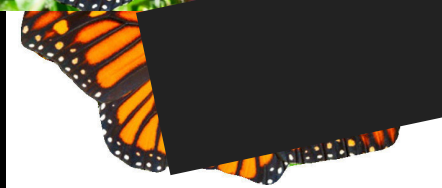
Segmentation



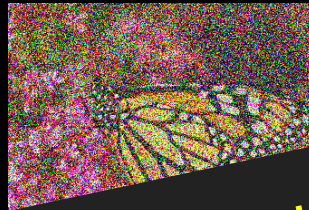
Denoising



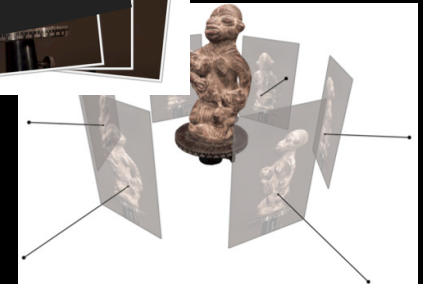
3D Reconstruction



Segmentation



Denoising



3D Reconstruction

Inverse Problems

Solving Strategy

Solving Strategy

Let Ω be the image space

$$u^* = \arg \min_{u \in \Omega} E(u)$$

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Model for denoising

Solving Strategy

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Model for denoising

$$E(u) = \alpha \|g - u\|^2 + \beta \|\nabla u\|^2,$$

where g is the noisy (input) image.

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← Solution resemble input image

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$$E(u) = \alpha \|g - u\|^2 + \beta \|\nabla u\|^2,$$

← Solution resemble input image

where g is the noisy (input) image.

← Solution should be smooth

Image segmentation

Image segmentation

Mumford-Shah model

Image segmentation

Mumford-Shah model

$$E(u, K) = \int_{\Omega-K} (g - u)^2 dx + \lambda \int_{\Omega-K} \|\nabla u\|^2 dx + \int_K dx$$

Image segmentation

Mumford-Shah model

$$E(u, K) = \int_{\Omega-K} (g - u)^2 dx + \lambda \int_{\Omega-K} \|\nabla u\|^2 dx + \int_K dx$$

↑
Similar to original image

Image segmentation

Mumford-Shah model

$$E(u, K) = \int_{\Omega-K} (g - u)^2 dx + \lambda \int_{\Omega-K} \|\nabla u\|^2 dx + \int_K dx$$

↗
Piecewise smooth

Image segmentation

Mumford-Shah model

$$E(u, K) = \int_{\Omega-K} (g - u)^2 dx + \lambda \int_{\Omega-K} \|\nabla u\|^2 dx + \int_K dx$$

↑
Small perimeter

Image segmentation

Mumford-Shah model

$$E(u, K) = \int_{\Omega-K} (g - u)^2 dx + \lambda \int_{\Omega-K} \|\nabla u\|^2 dx + \int_K dx$$

Binary piece-wise smooth [**Chan; Vese, 2001**]

Image segmentation

Mumford-Shah model

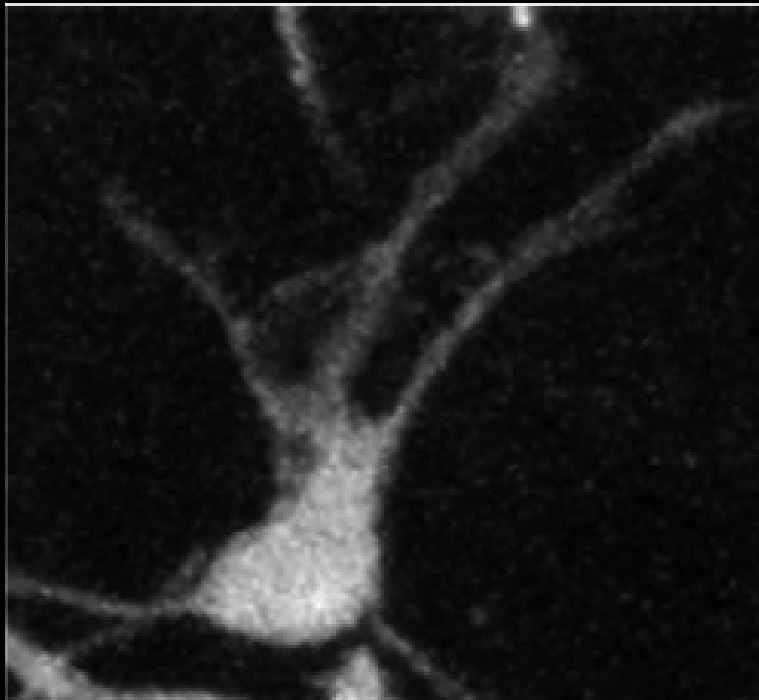
$$E(u, K) = \int_{\Omega-K} (g - u)^2 dx + \lambda \int_{\Omega-K} \|\nabla u\|^2 dx + \int_K dx$$

Binary piece-wise smooth [**Chan; Vese, 2001**]

Optimization of Ambrosio Tortorelli energy [**Foare; Lachaud; Talbot, 2016**]

Curvature as regularization in segmentation

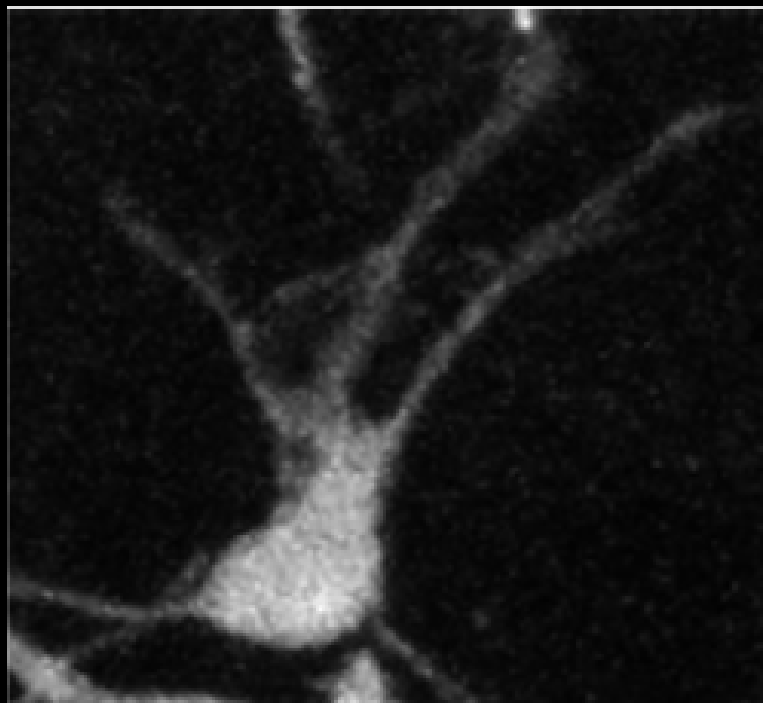
Curvature as regularization in segmentation



[El-Zehiry, 2010]

Curvature as regularization in segmentation

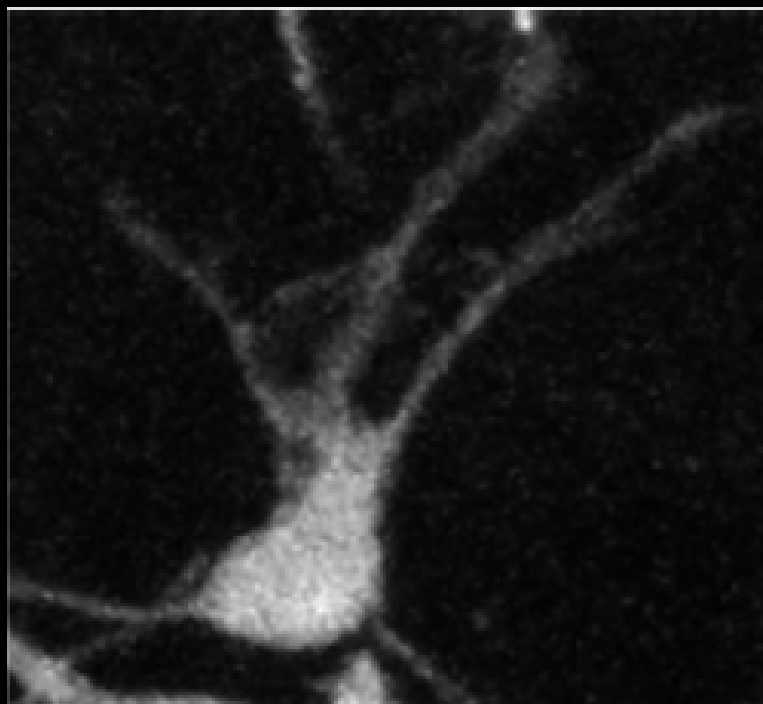
Data term



[El-Zehiry, 2010]

Curvature as regularization in segmentation

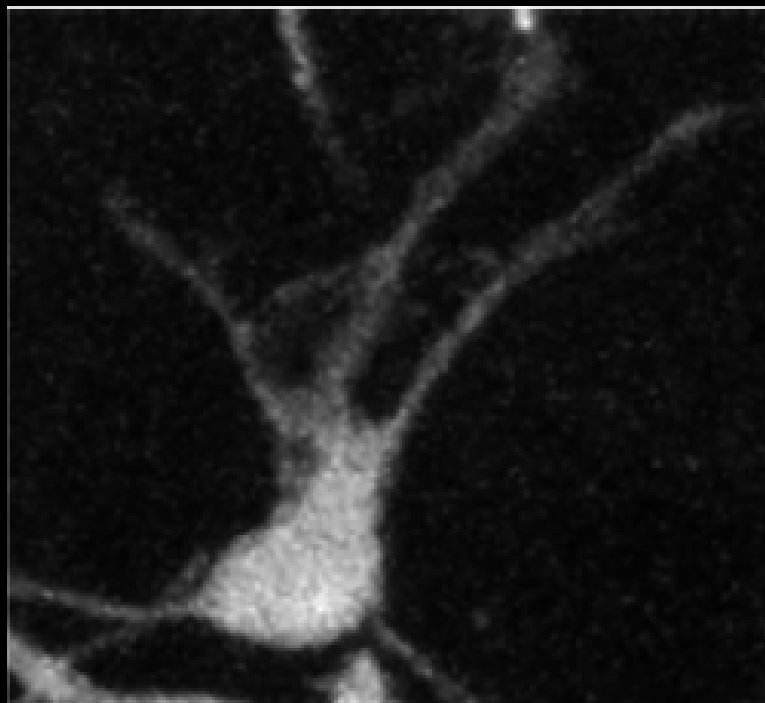
Data + Perimeter term



[El-Zehiry, 2010]

Curvature as regularization in segmentation

Data + Curvature term

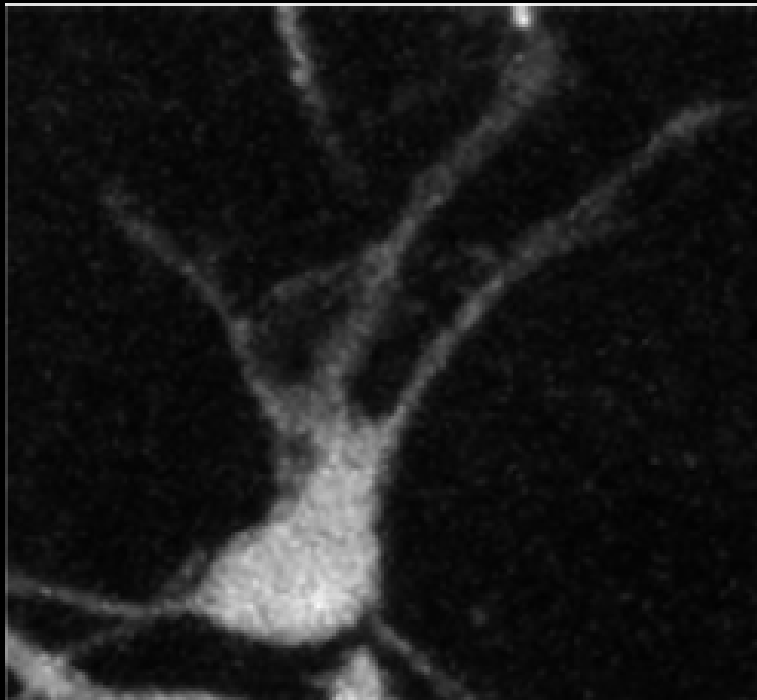


[El-Zehiry, 2010]



Curvature as regularization in segmentation

Data + Curvature term



[El-Zehiry, 2010]



Completion property

Curvature as regularization in segmentation

Curvature as regularization in segmentation

$$E(u) = \int_{\Omega} (u - g)^2 dx + \int_{\partial u} \alpha + \beta \kappa^2 ds$$

Curvature as regularization in segmentation

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Elastica energy

Curvature as regularization in segmentation

$$E(u) = \int_{\Omega} (u - g)^2 dx + \int_{\partial u} \alpha + \beta \kappa^2 ds$$

Elastica energy

Non-convex term

Curvature as regularization in segmentation

$$E(u) = \int_{\Omega} (u - g)^2 dx + \int_{\partial u} \alpha + \beta \kappa^2 ds$$

Elastica energy

The diagram shows the equation $E(u) = \int_{\Omega} (u - g)^2 dx + \int_{\partial u} \alpha + \beta \kappa^2 ds$. An orange bracket above the second integral is labeled "Elastica energy". A green arrow points from the text "Integration domain is unknown" to the ∂u term in the second integral. Another green arrow points from the text "Non-convex term" to the $\beta \kappa^2$ term in the second integral.

Curvature as regularization in segmentation

$$E(u) = \int_{\Omega} (u - g)^2 dx + \int_{\partial u} \alpha + \beta \kappa^2 ds$$

Elastica energy

Integration domain is unknown

Non-convex term

Difficult to optimize

Curvature as regularization in segmentation

$$E(u) = \int_{\Omega} (u - g)^2 dx + \int_{\partial u} \alpha + \beta \kappa^2 ds$$

Elastica energy

Integration domain is unknown

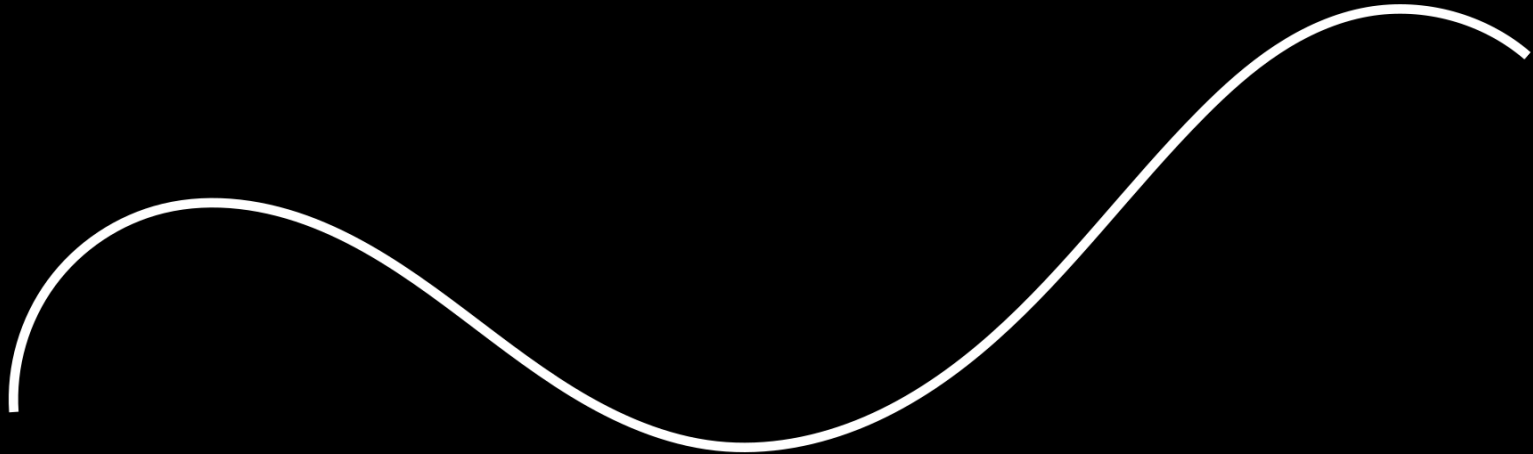
Non-convex term

Difficult to optimize

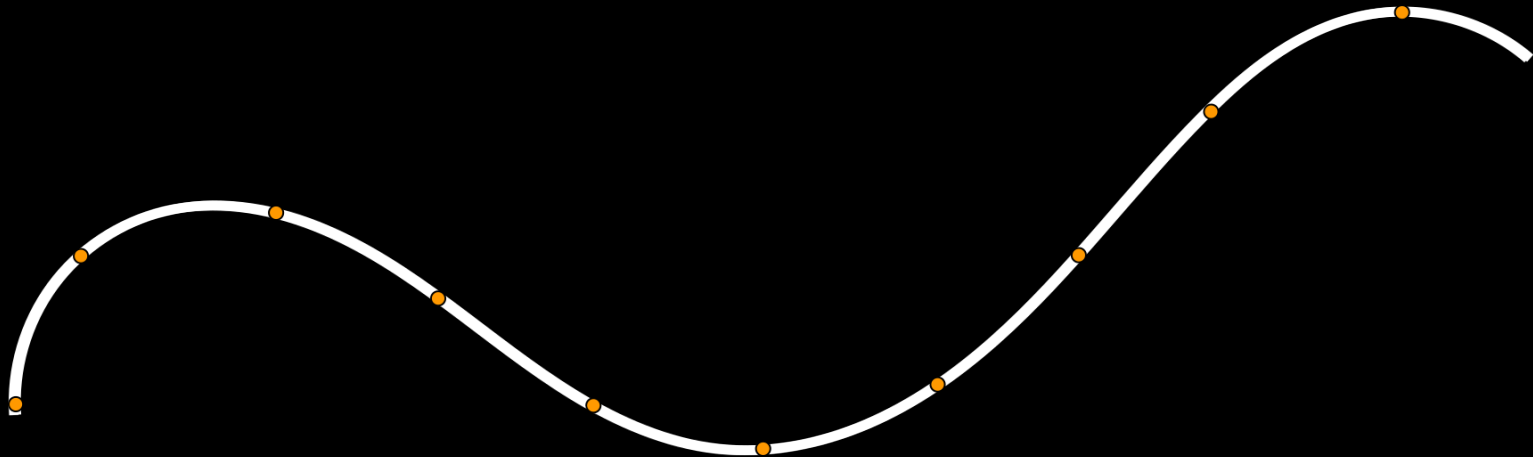
Second order term. Should be careful with discretization scheme

Curvature discretization

Curvature discretization

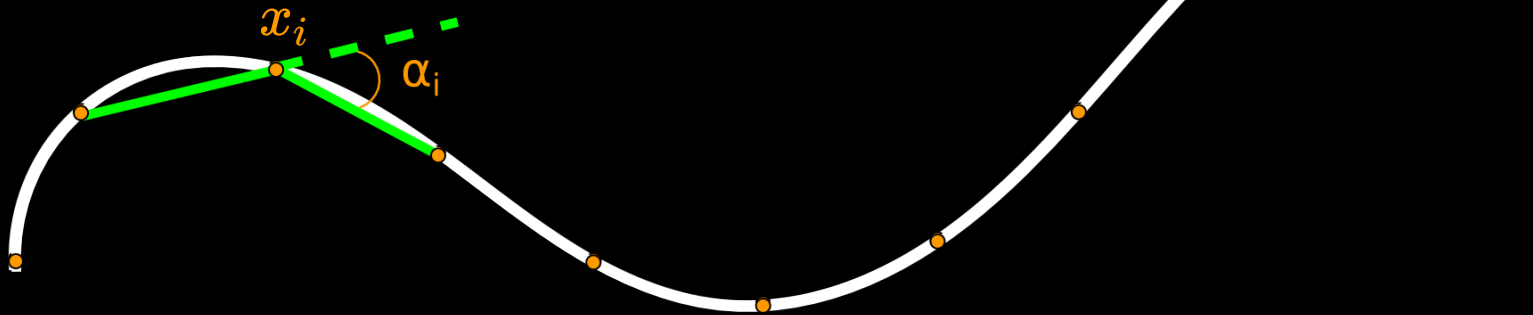


Curvature discretization



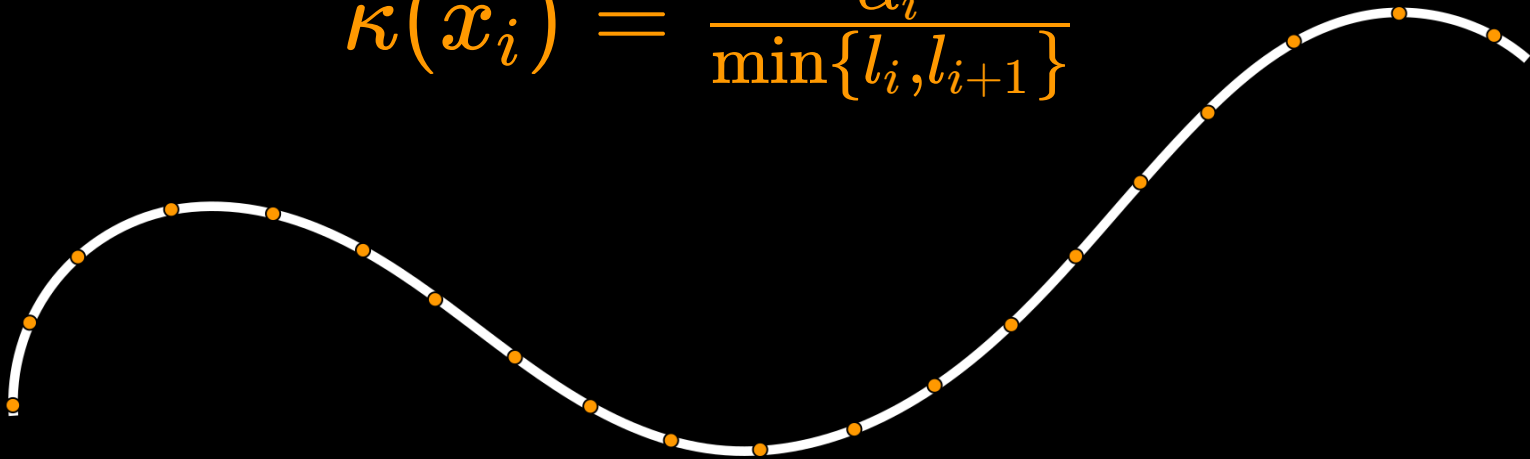
Curvature discretization

$$\hat{\kappa}(x_i) = \frac{\alpha_i}{\min\{l_i, l_{i+1}\}}$$



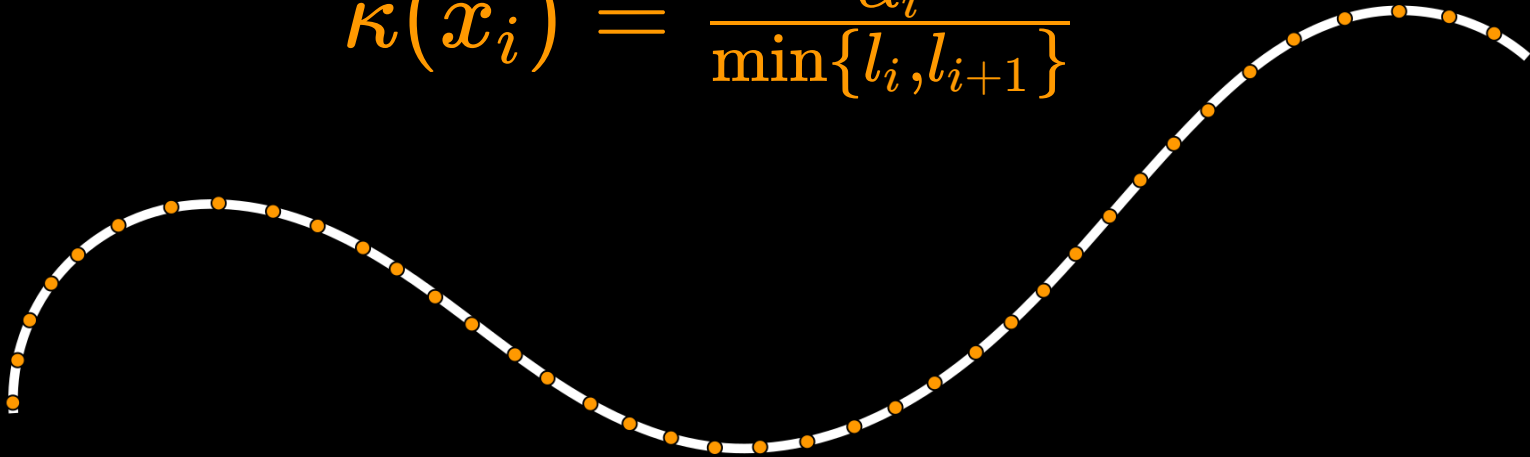
Curvature discretization

$$\hat{\kappa}(x_i) = \frac{\alpha_i}{\min\{l_i, l_{i+1}\}}$$

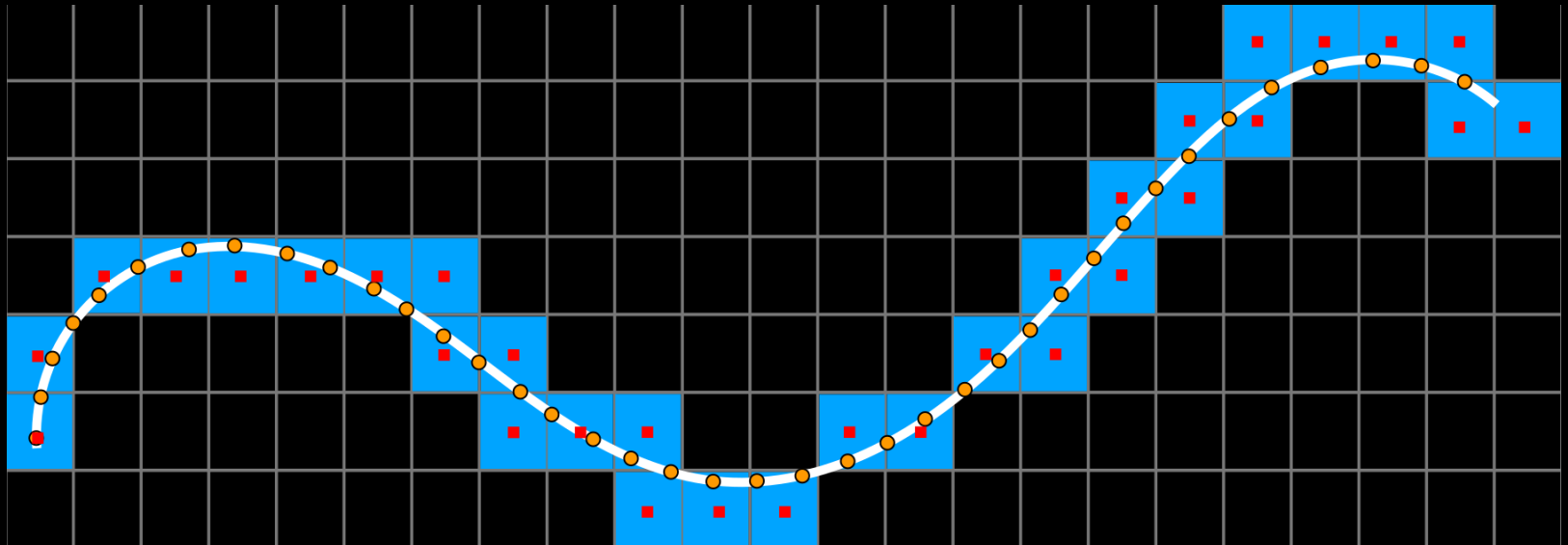


Curvature discretization

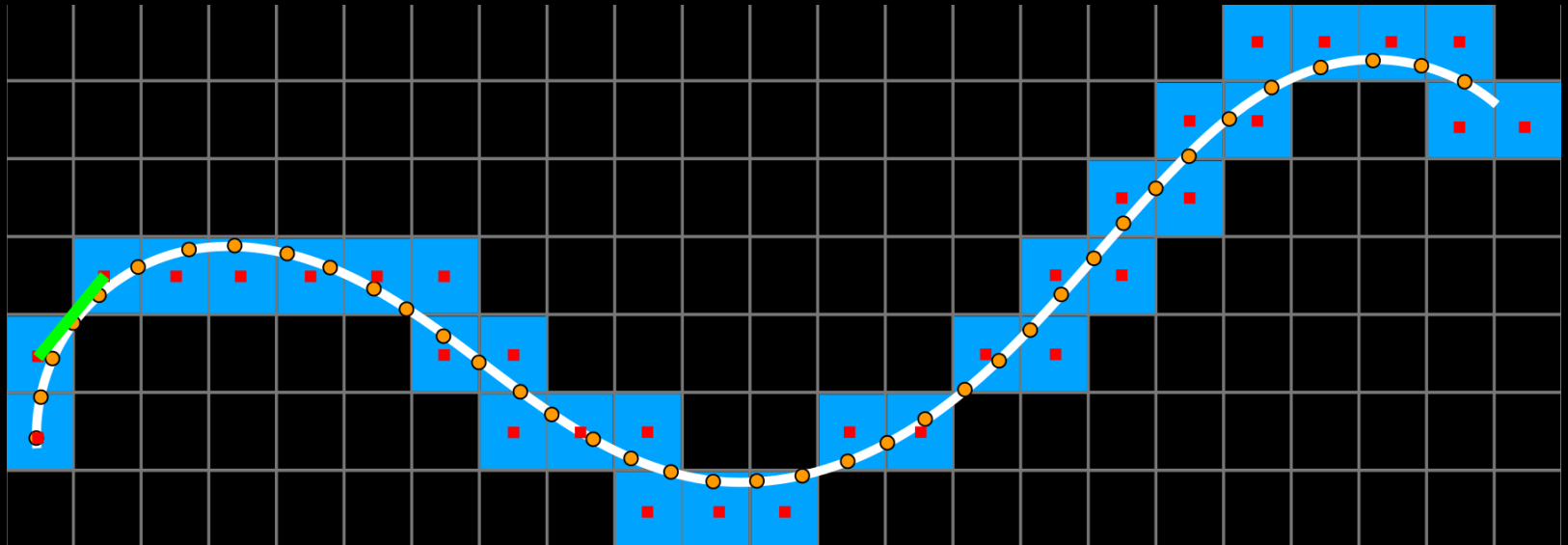
$$\hat{\kappa}(x_i) = \frac{\alpha_i}{\min\{l_i, l_{i+1}\}}$$



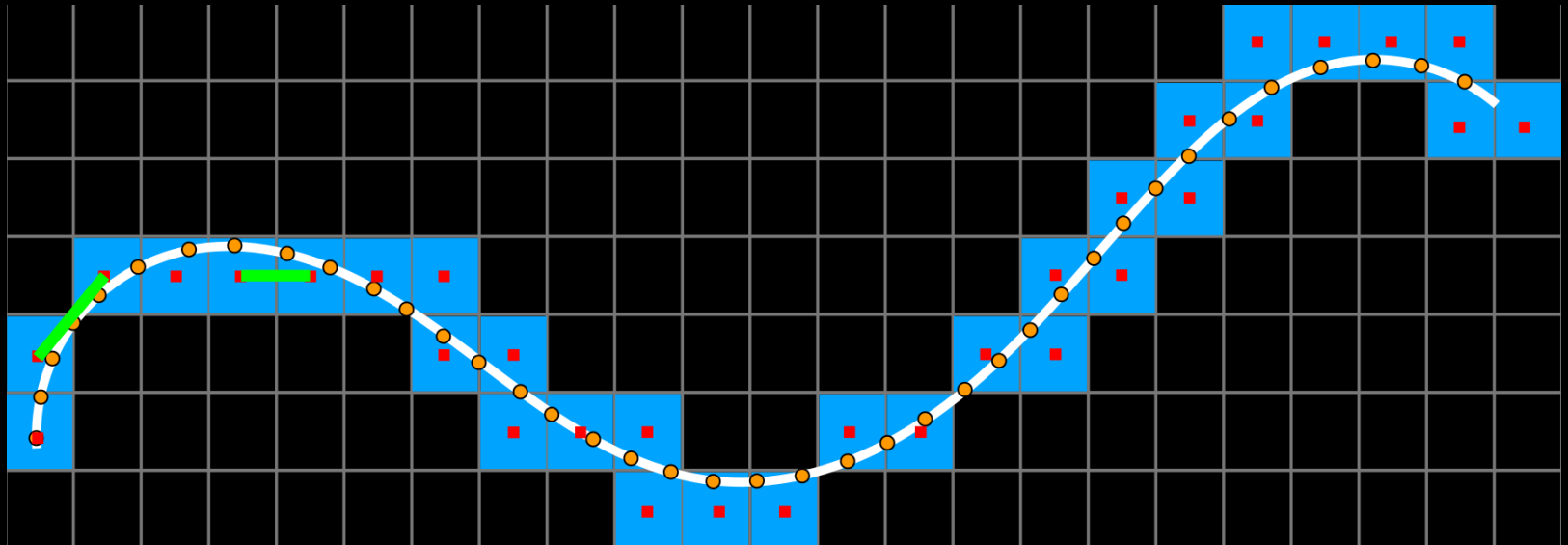
Curvature discretization



Curvature discretization

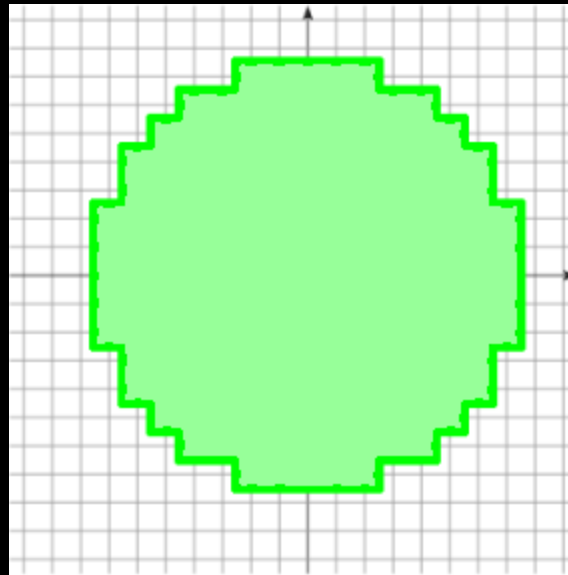


Curvature discretization



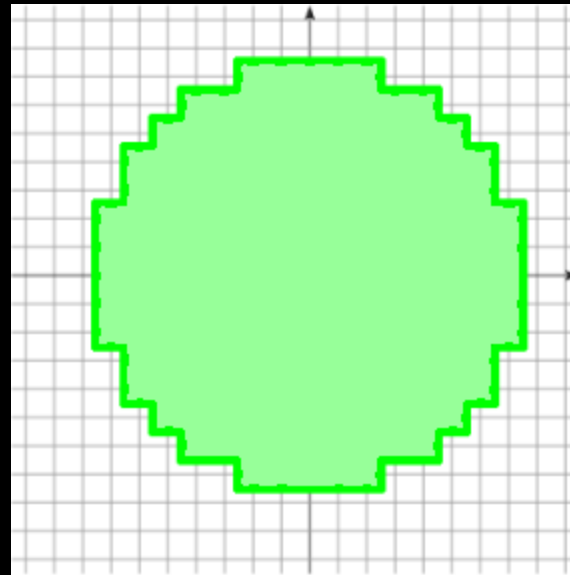
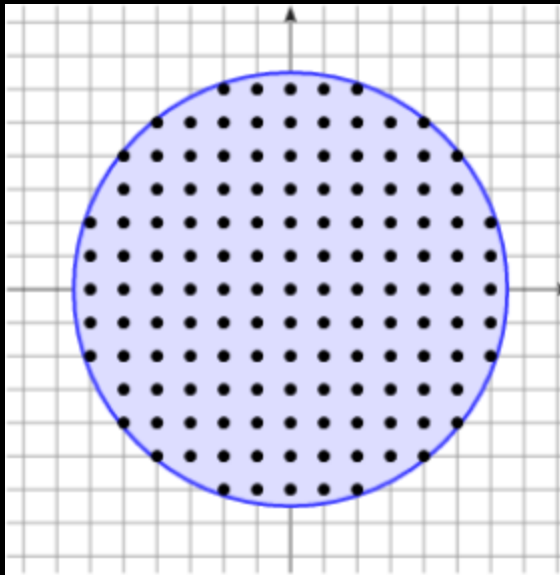
Digitization ambiguity

Digitization ambiguity



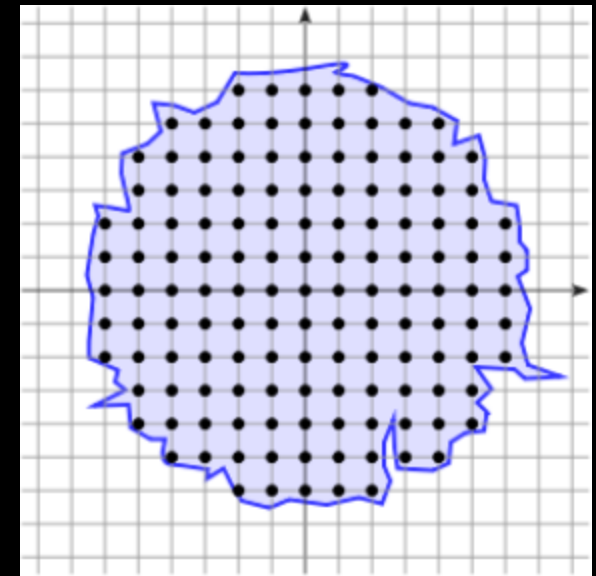
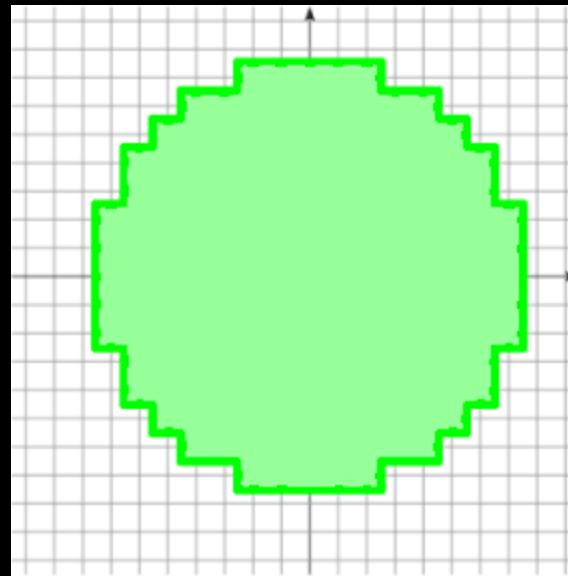
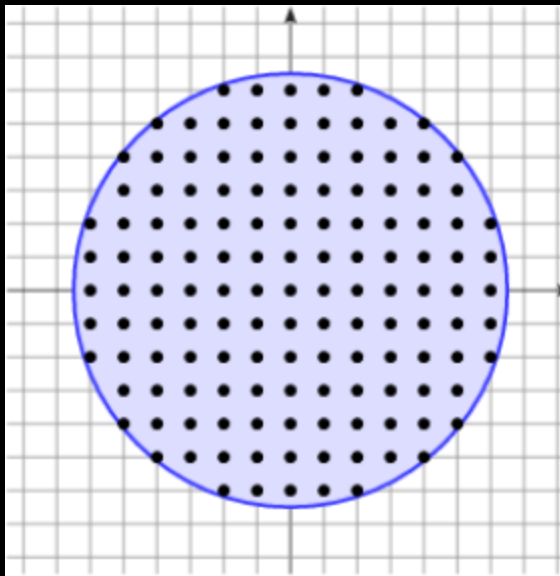
[Roussillon, Lachaud 2011]

Digitization ambiguity



[Roussillon, Lachaud 2011]

Digitization ambiguity



[Roussillon, Lachaud 2011]

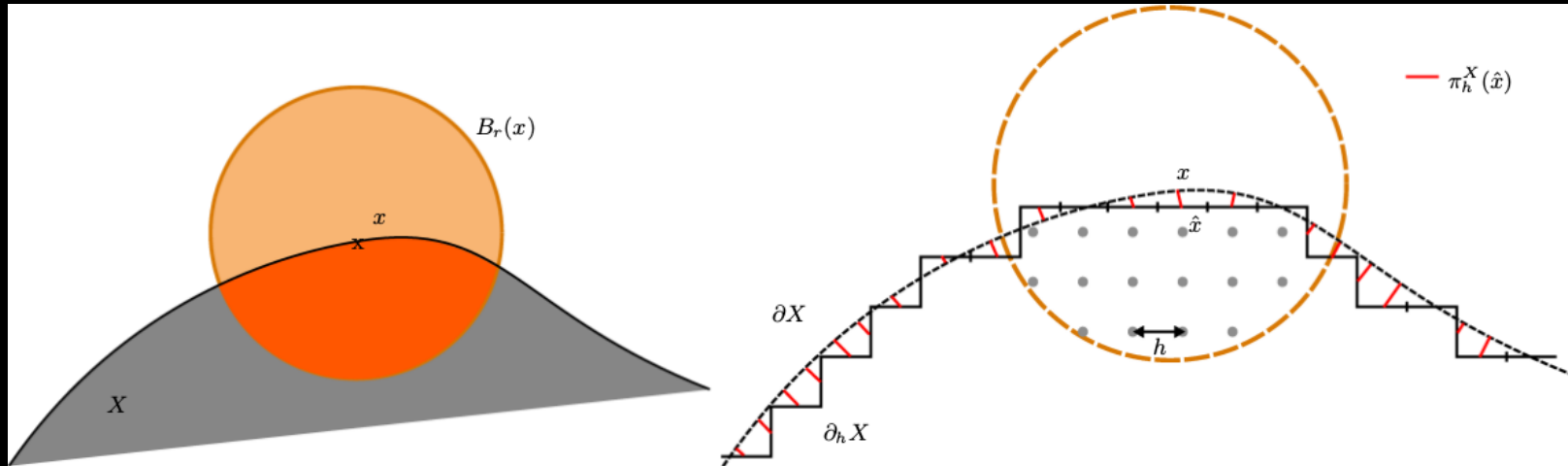
Multigrid Convergence

Multigrid Convergence

The estimated quantity $\hat{E}(D_h(X), \hat{x}, h)$ gets arbitrarily close from $E(X, x)$ as resolution increases.

Integral based estimator for curvature

Integral based estimator for curvature



[Coeurjolly, Lachaud, Levallois 2013]

$$\hat{\kappa}_{R,h}(x_i) = \frac{3}{R^3} \left(\frac{\pi R^2}{2} - \widehat{Area}(B_{R,h}(x_i) \cap D_h) \right)$$

To sum up

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We want to use curvature as regularization term in models of image processing tasks

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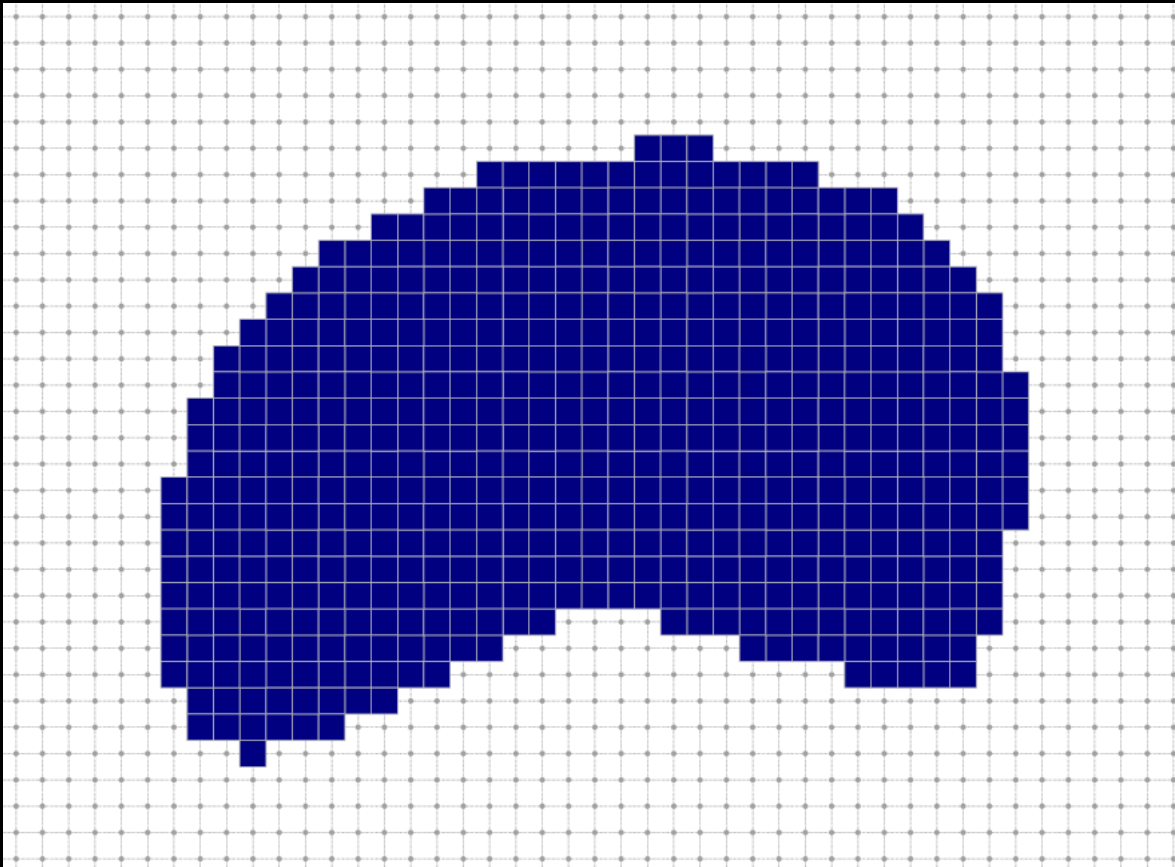
We want to use curvature as regularization term in models of image processing tasks

We believe that by using a multigrid convergent estimator, we can recover better results

Notation

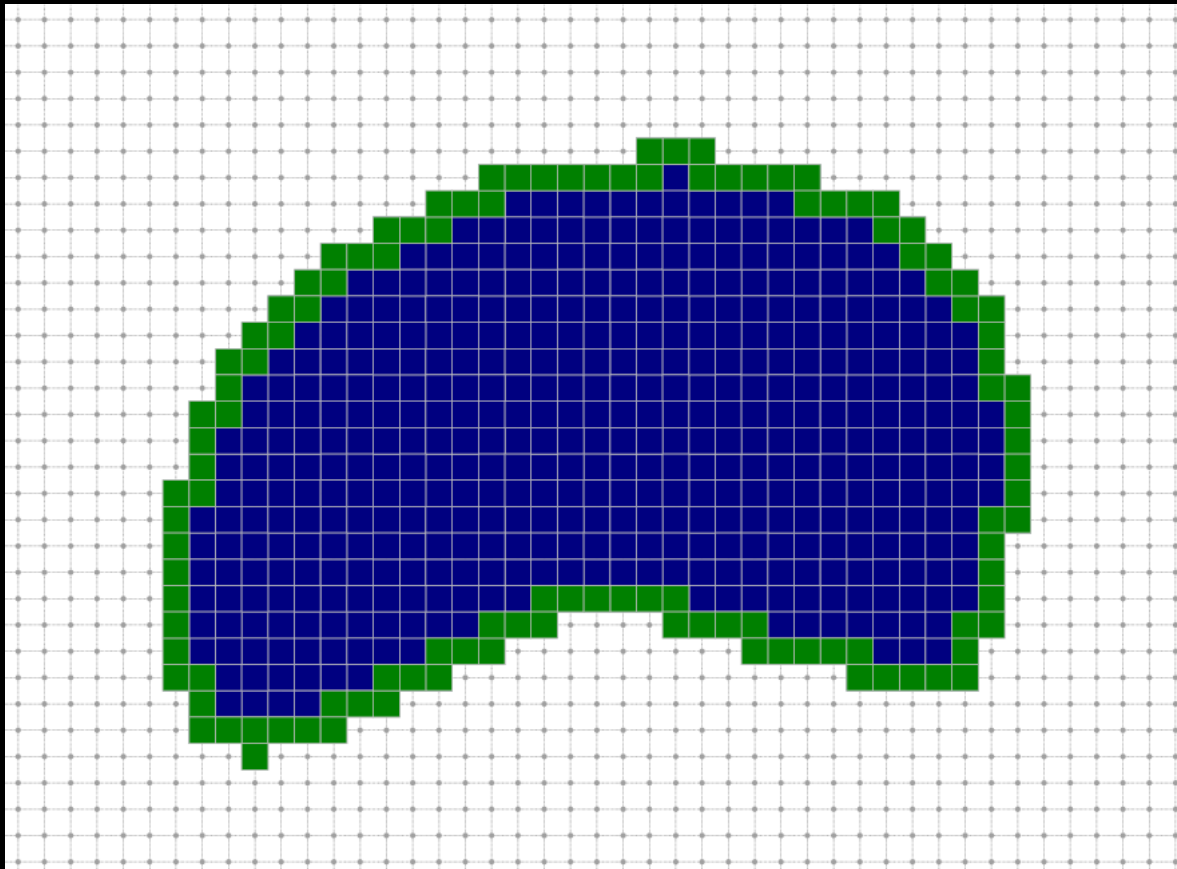
Notation

Let D be a connected digital shape



Notation

Let D be a connected digital shape

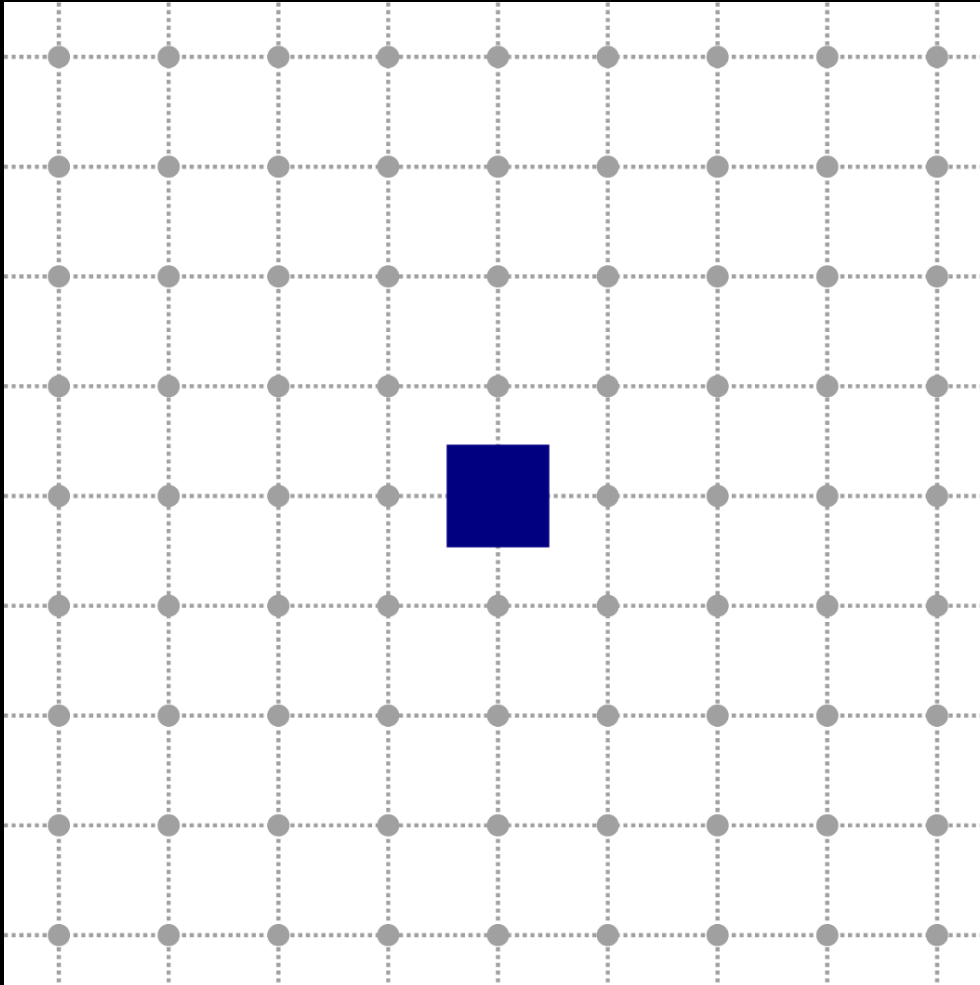


$\mathcal{C}(D)$

4-connected pixel
boundary

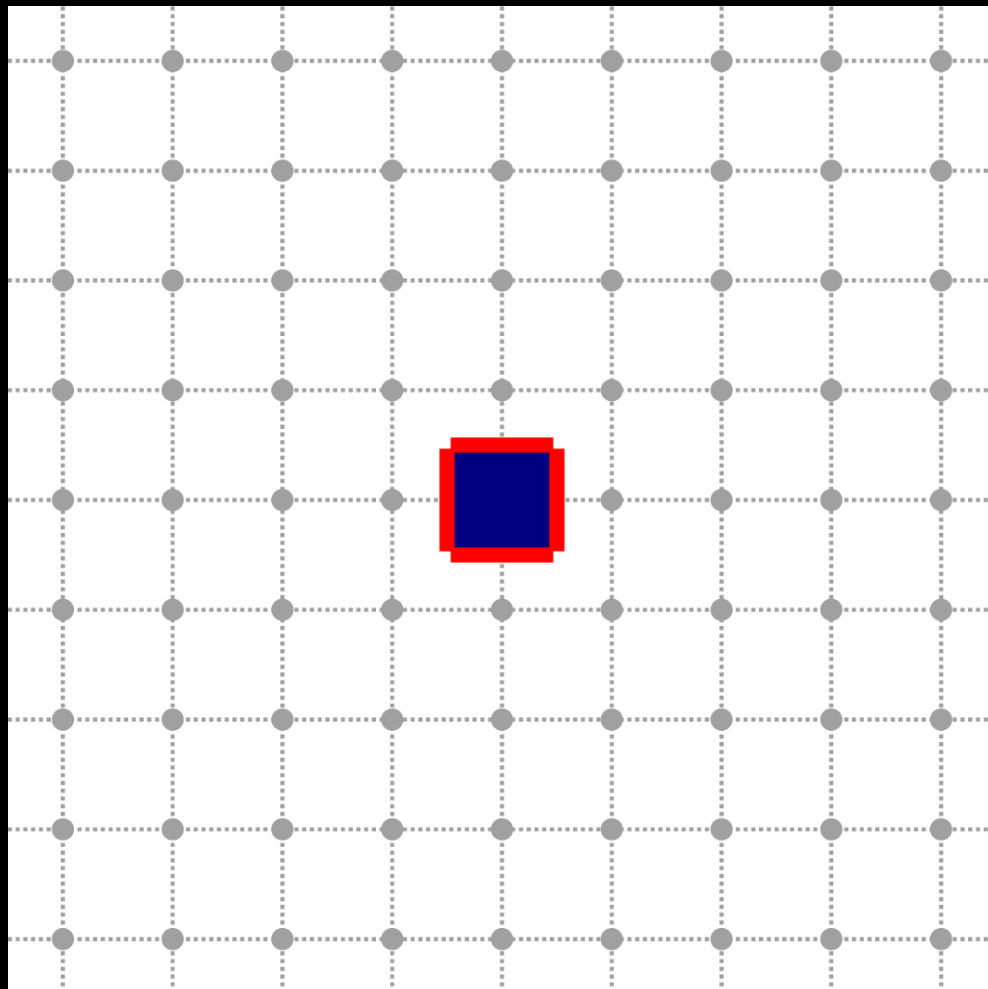
Cellular grid model

Cellular grid model



Cells (pixels)

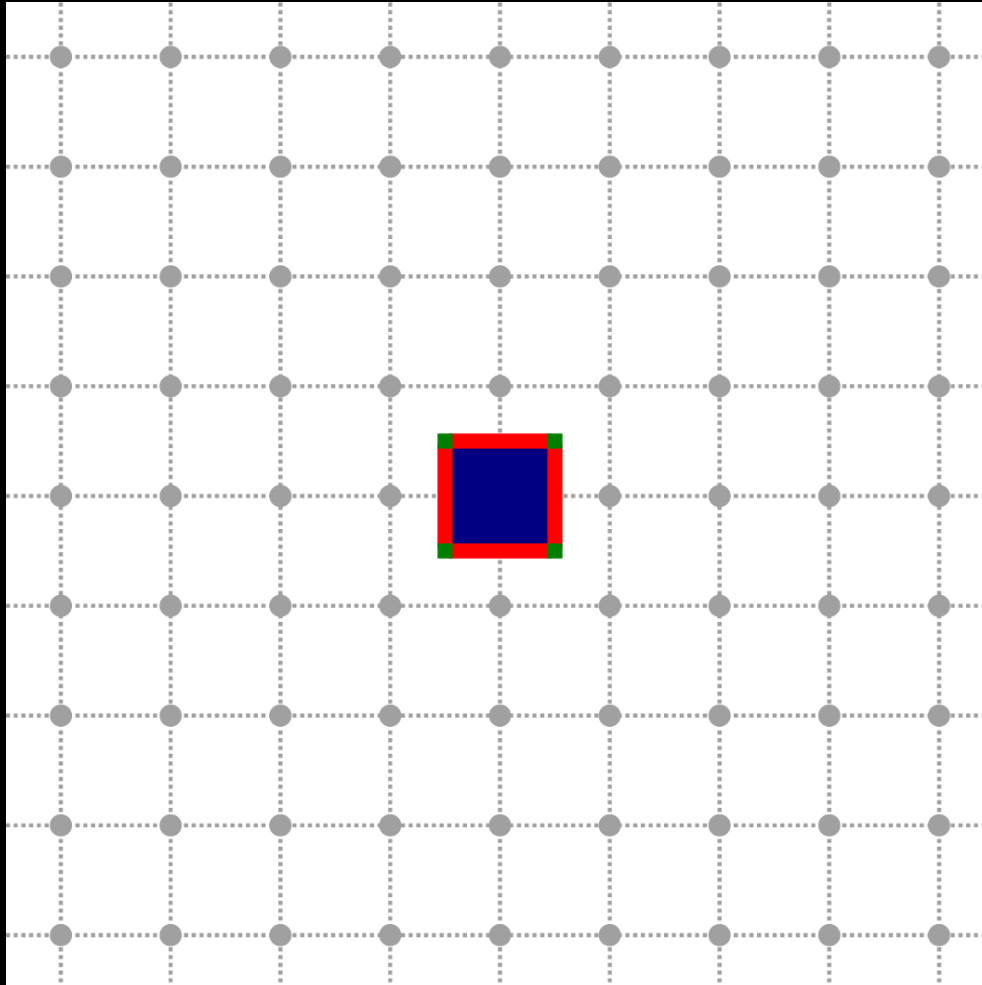
Cellular grid model



Cells (pixels)

Linels

Cellular grid model



Cells (pixels)

Linels

Pointels

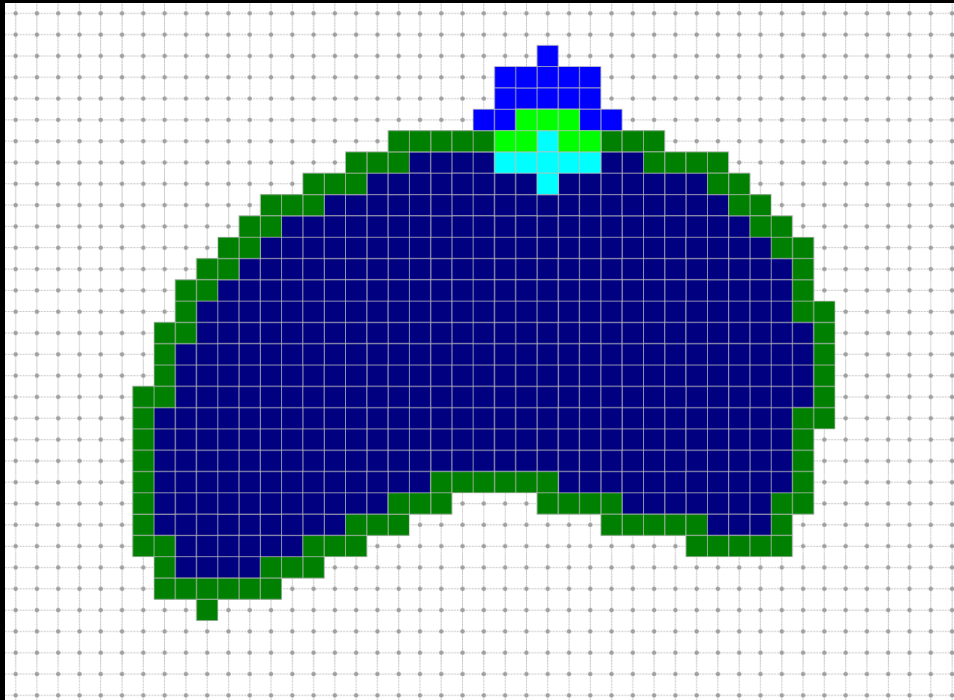
Curve evolution model

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$$E(u) = \int_{\partial u} \kappa^2 ds$$

Curve evolution model

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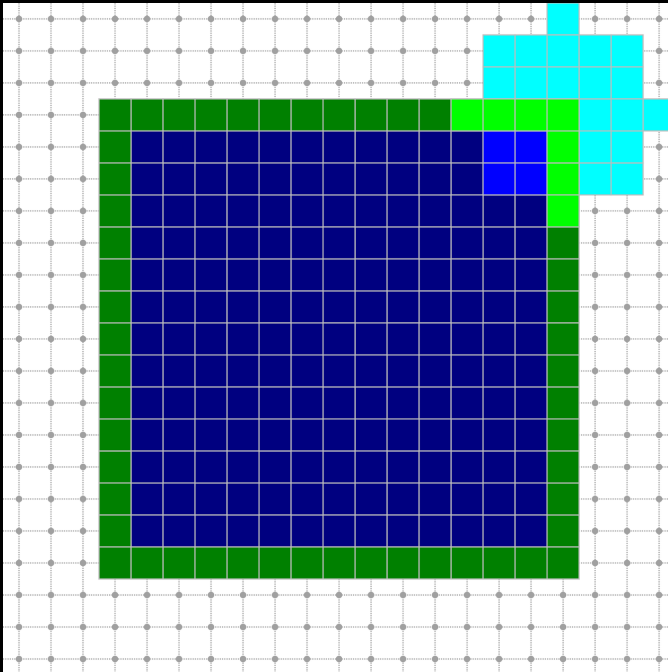


$$\sum_{y_i \in \mathcal{C}(D)} \hat{k}_R^2(y_i)$$

Curve evolution model

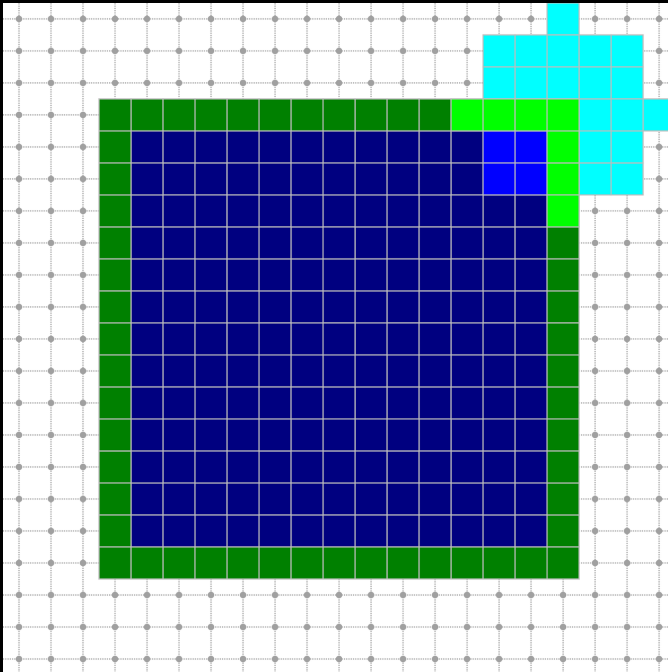
Curve evolution model

$$\min_y \sum_{y_i \in \mathcal{C}(D)} \hat{k}_R^2(y_i), \quad y \in \{0, 1\}^{|\mathcal{C}(D)|}$$



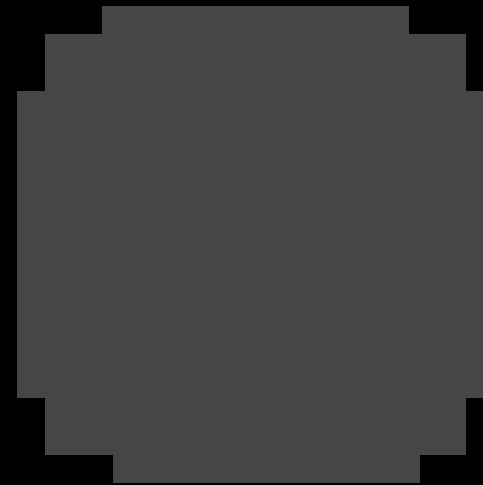
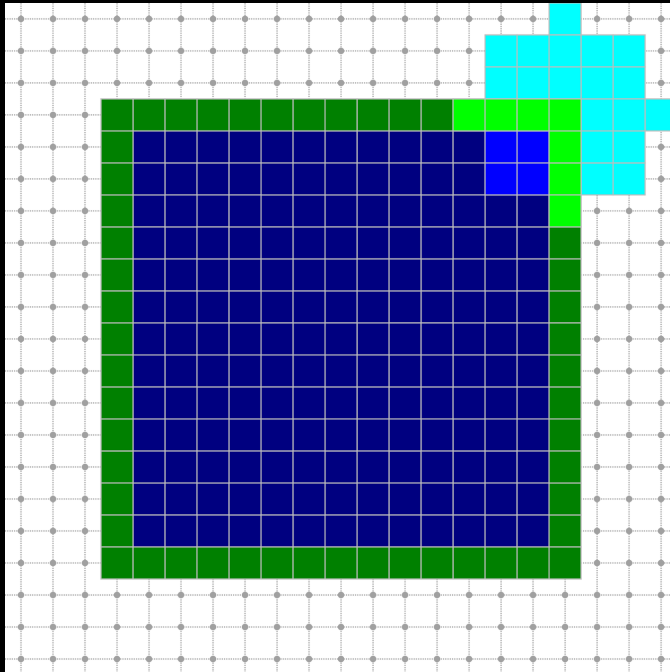
Curve evolution model

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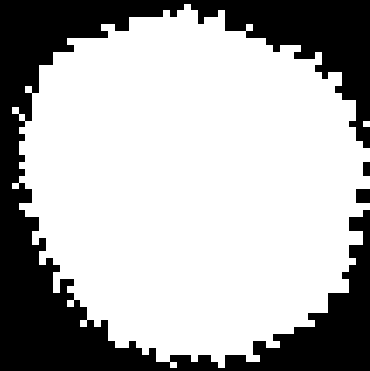
Curve evolution model

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A first evolution

A first evolution

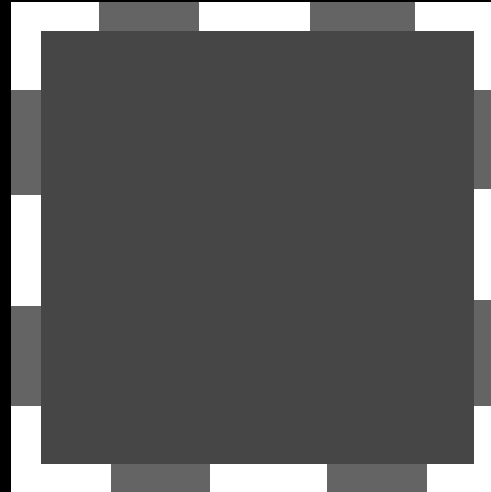


Sensible regions indication

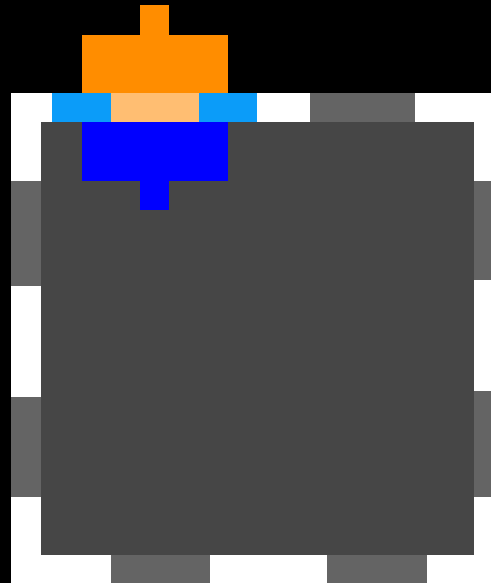
Sensible regions indication



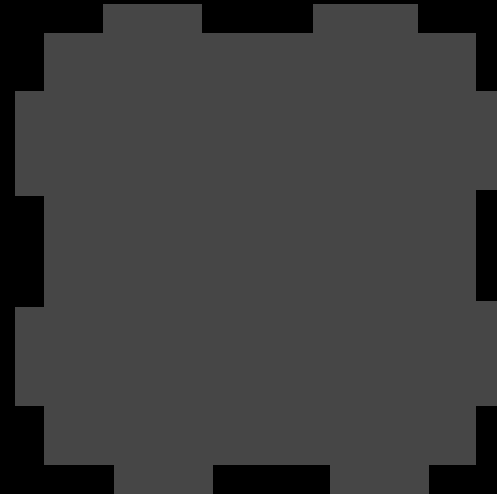
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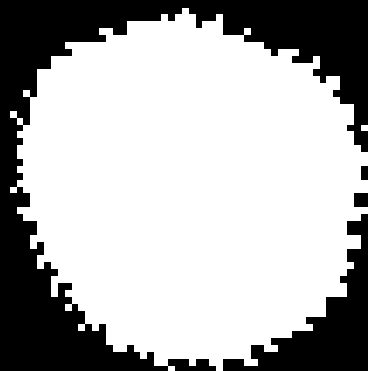
Sensible regions indication



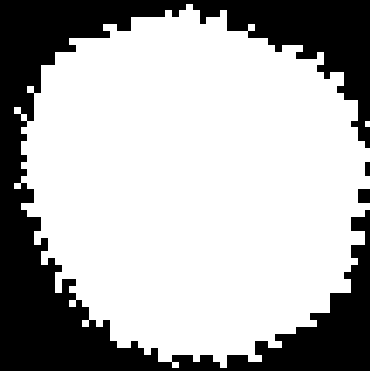
Perimeter penalization

Perimeter penalization

$$\min_y \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i)$$



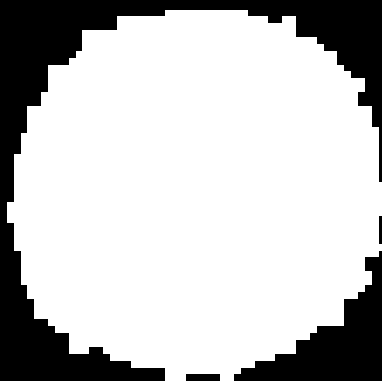
Perimeter penalization



$$\min_y \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i)$$

$$\min_y \alpha \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i) + \beta \sum_{y_i \in \mathcal{O}} \sum_{y_j \in \mathcal{N}_4(y_i)} (y_i - y_j)^2$$

Perimeter penalization

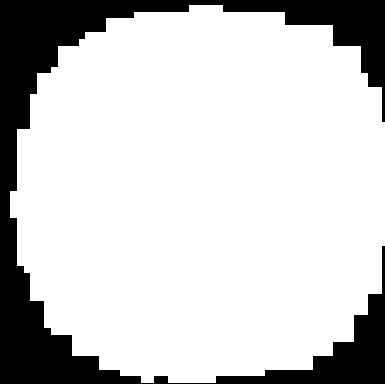


$$\alpha = 1$$
$$\beta = 0.5$$

$$\min_y \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i)$$

$$\min_y \alpha \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i) + \beta \sum_{y_i \in \mathcal{O}} \sum_{y_j \in \mathcal{N}_4(y_i)} (y_i - y_j)^2$$

Perimeter penalization

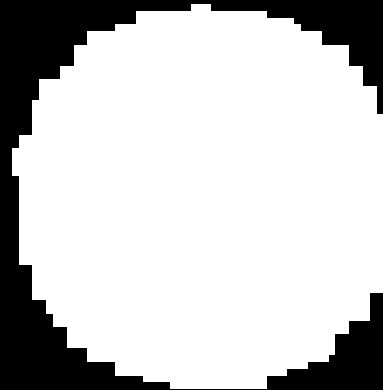


$$\alpha = 1$$
$$\beta = 1.0$$

$$\min_y \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i)$$

$$\min_y \alpha \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i) + \beta \sum_{y_i \in \mathcal{O}} \sum_{y_j \in \mathcal{N}_4(y_i)} (y_i - y_j)^2$$

Perimeter penalization

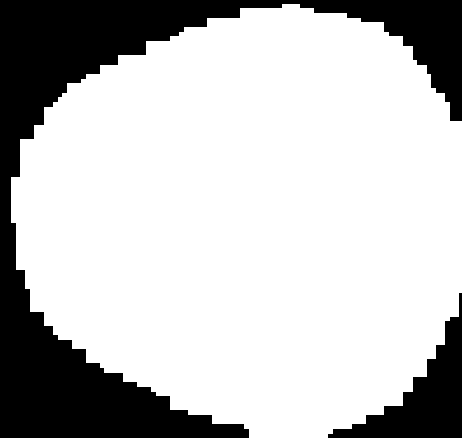


$$\alpha = 1$$
$$\beta = 2.0$$

$$\min_y \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i)$$

$$\min_y \alpha \sum_{y_i \in \mathcal{O}} \hat{k}_R^2(y_i) + \beta \sum_{y_i \in \mathcal{O}} \sum_{y_j \in \mathcal{N}_4(y_i)} (y_i - y_j)^2$$

Perimeter penalization

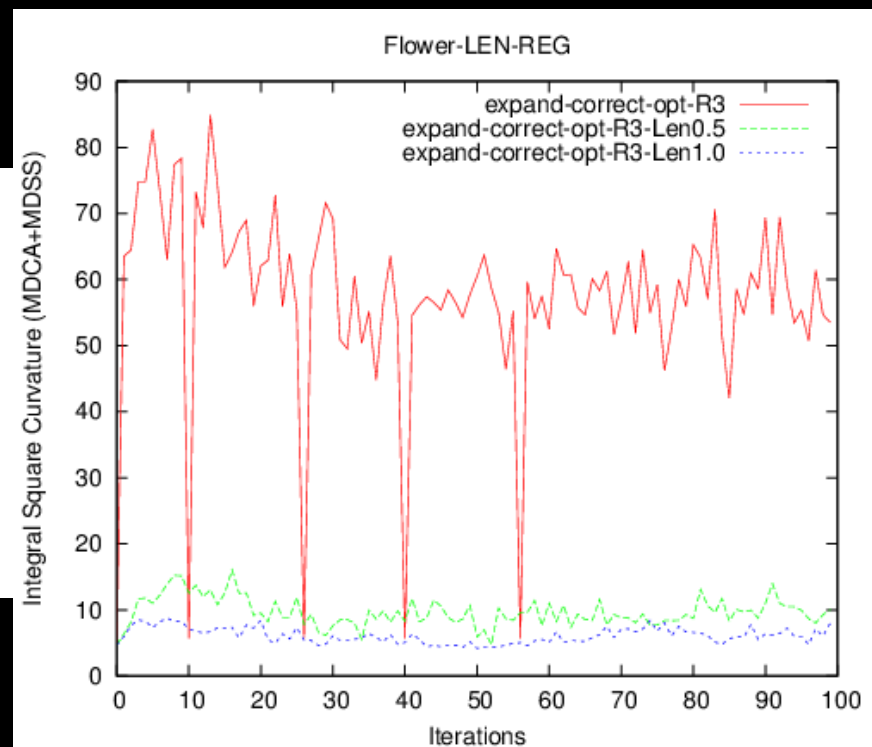
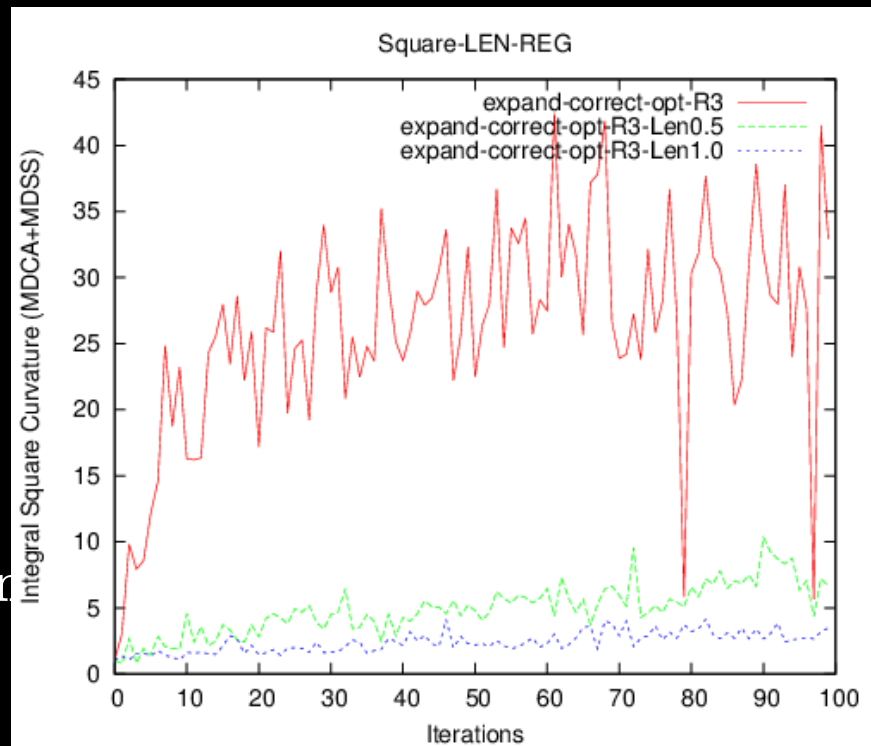


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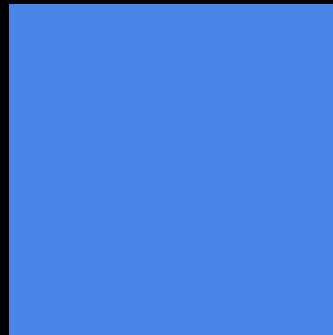
Perimeter penalization



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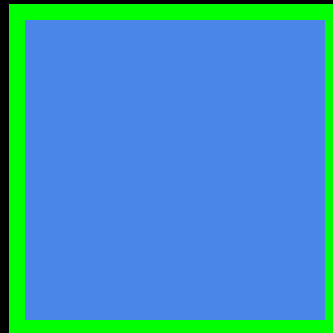
Filtering artifacts

Filtering artifacts



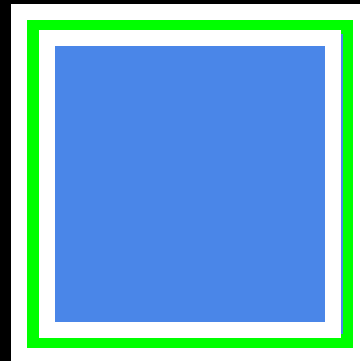
Filtering artifacts

Optimization region 



Filtering artifacts

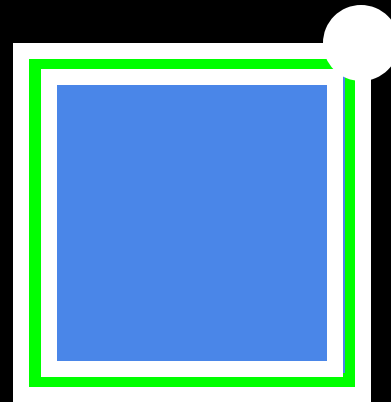
Optimization region \mathcal{O}



Computation Region \mathcal{A}

Filtering artifacts

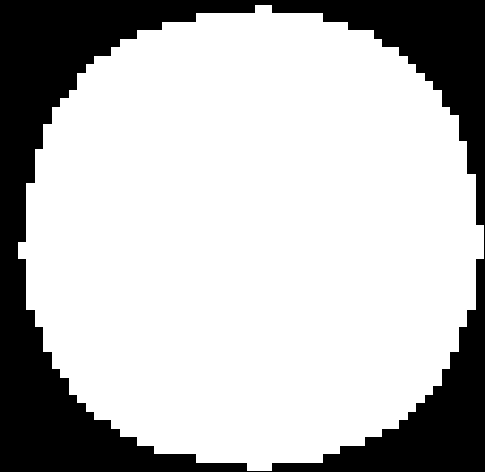
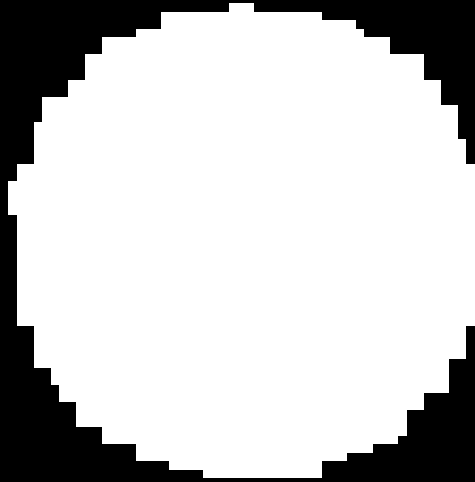
Optimization region \mathcal{O}



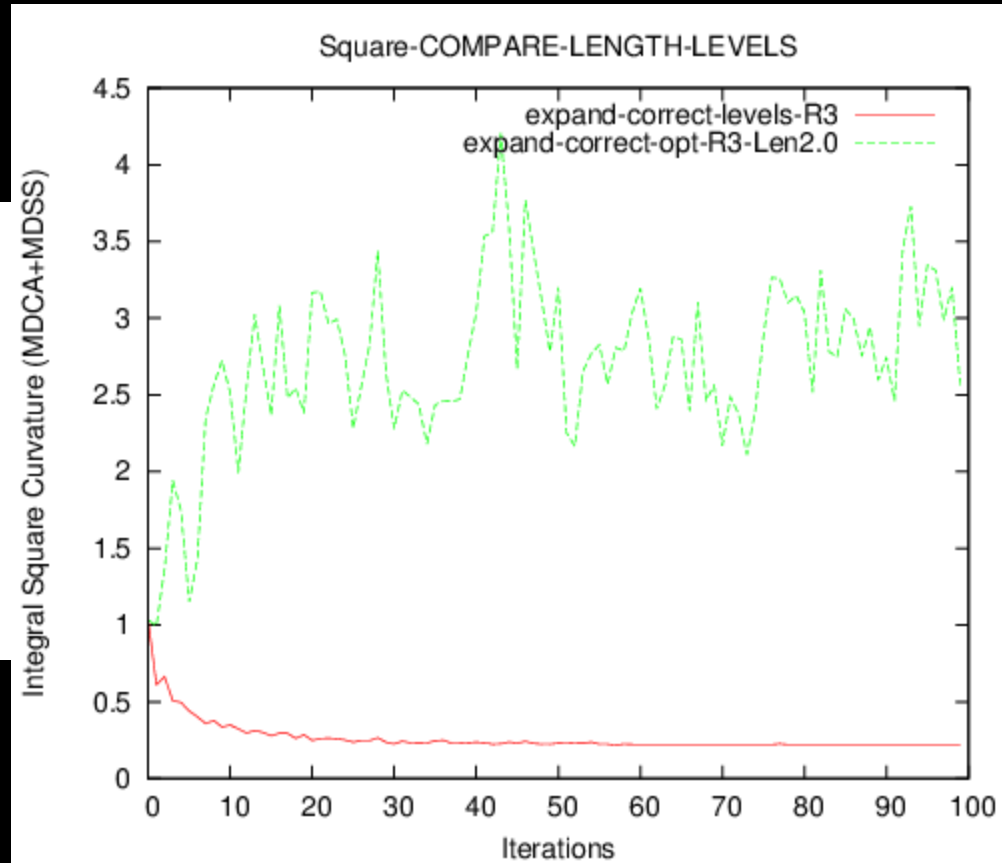
Computation Region \mathcal{A}

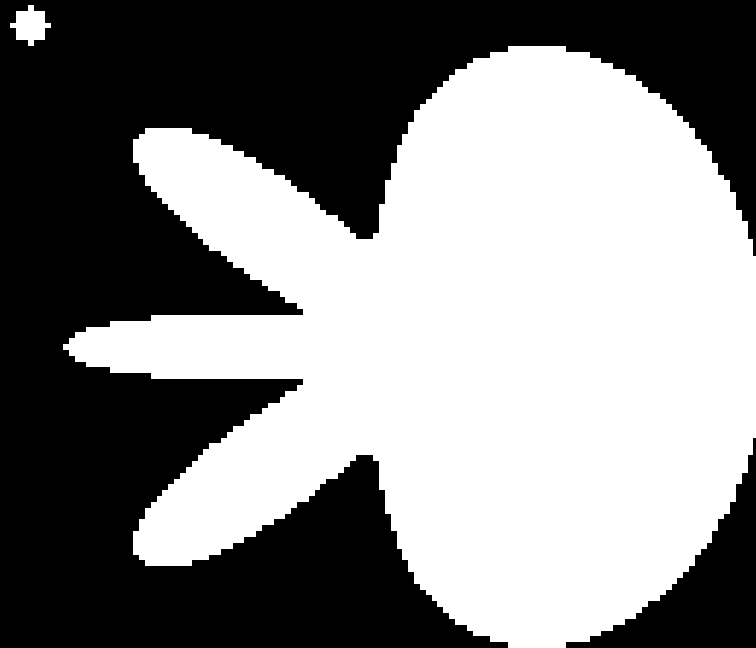
$$\min_y \sum_{a_i \in \mathcal{A}(D)} \hat{k}_R^2(a_i, y), \quad y \in \{0, 1\}^{|\mathcal{C}(D)|}$$

Bands evolution

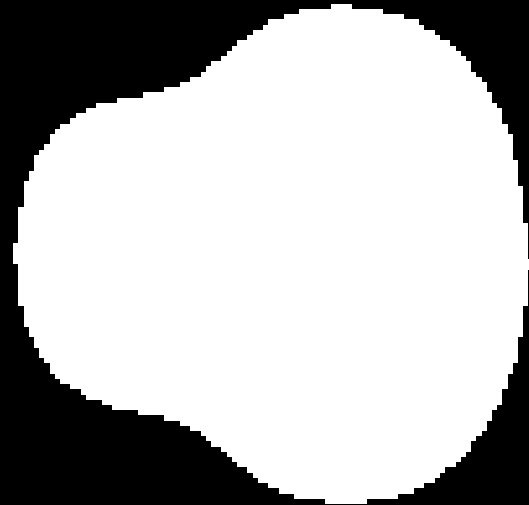
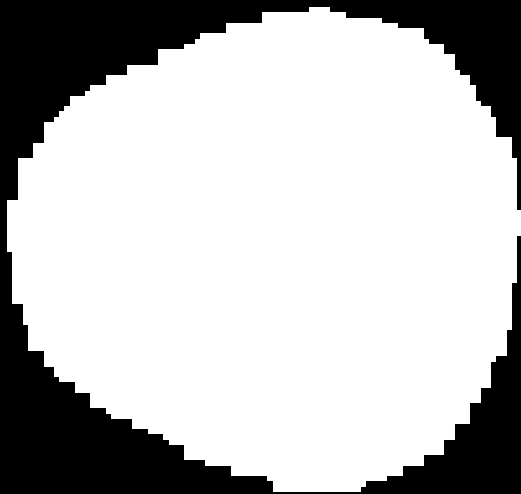


Bands evolution

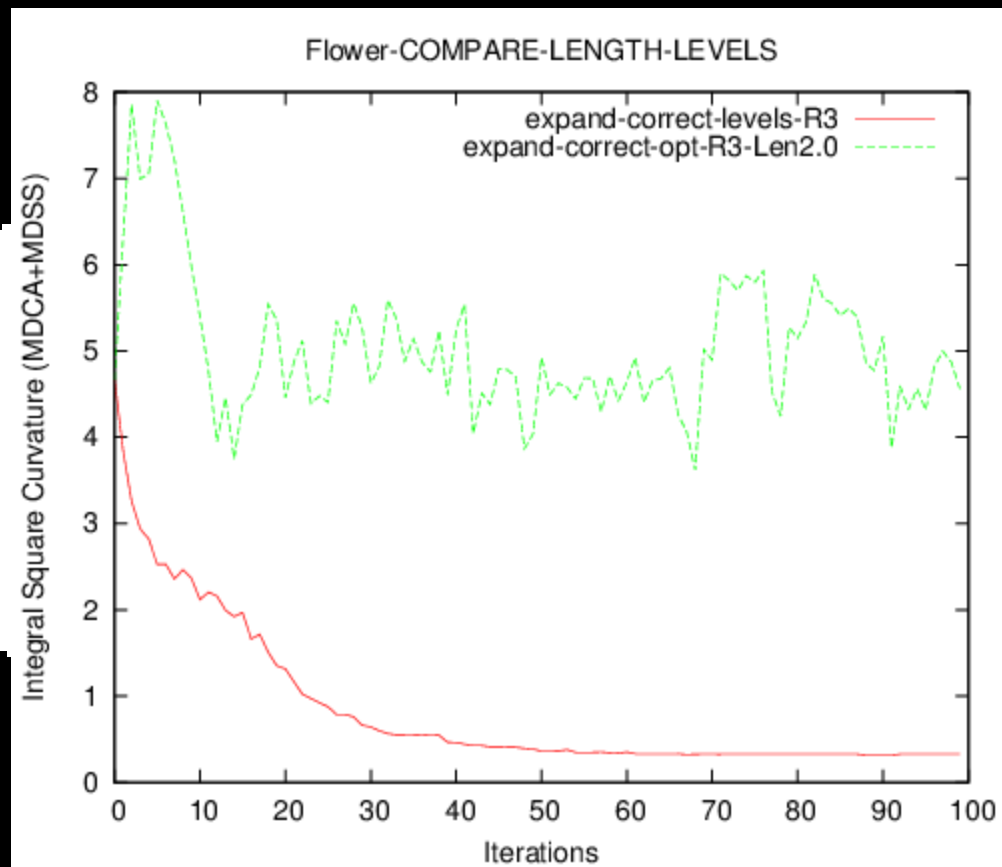




Bands evolution

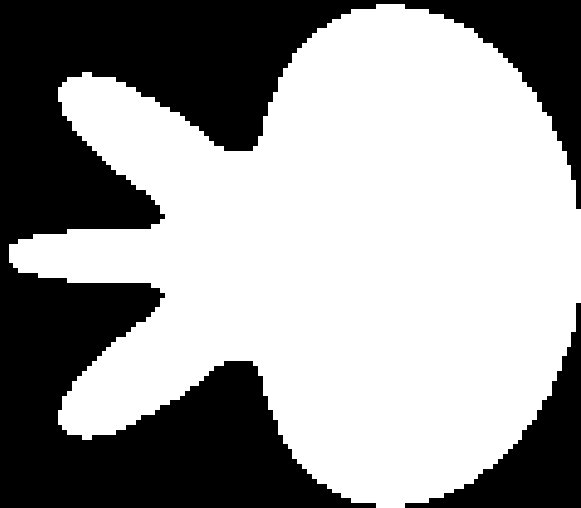


Bands evolution

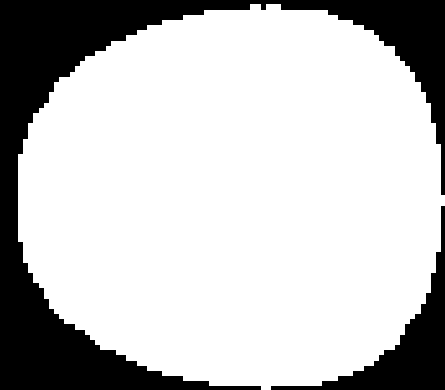


Ball radius effect

$$R = 3$$

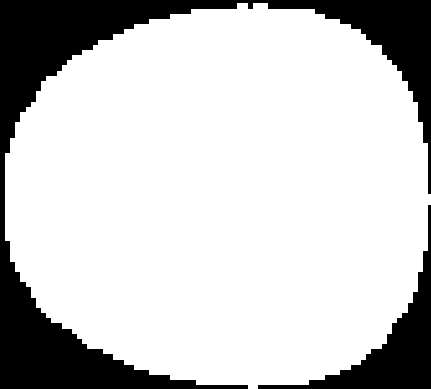


$$R = 5$$

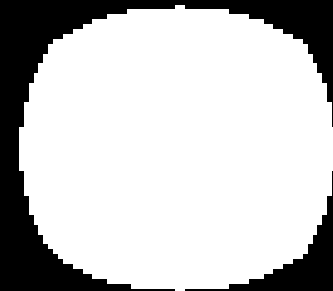


Ball radius effect

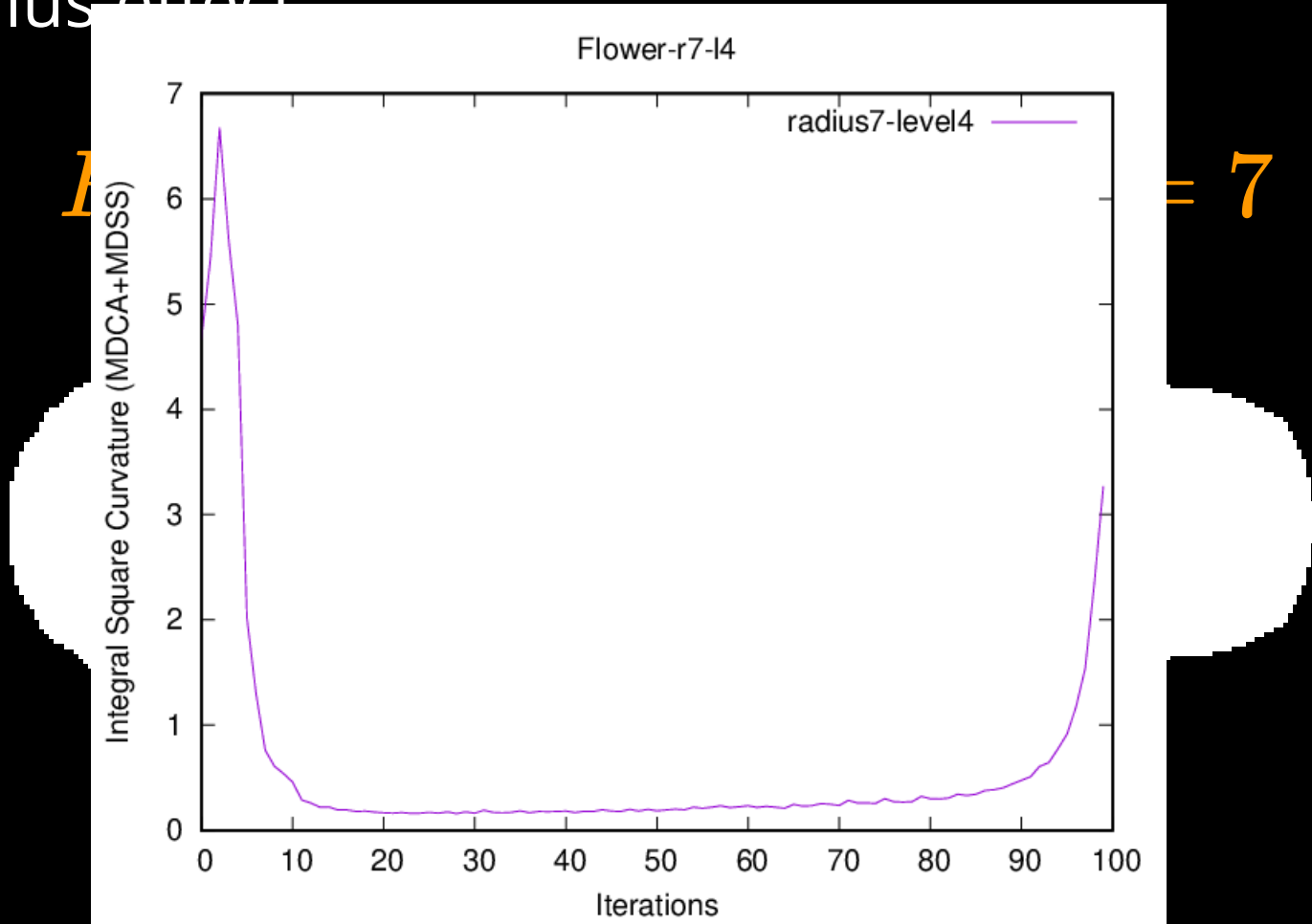
$$R = 5$$



$$R = 7$$



Ball radius effect



Quadratic pseudo-boolean function

Quadratic pseudo-boolean function

$$\min_y \sum_{y_i \in \mathcal{C}(D)} \hat{k}_R^2(y_i)$$

Quadratic pseudo-boolean function

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$$\min_y \sum_{p \in \mathcal{C}(D)} \left((1/2 + |F_r(p)| - c_2) \cdot \sum_{y_i \in Y_r(p)} y_i + \sum_{y_i, y_j \in Y_r(p); i < j} y_i y_j \right)$$

Quadratic pseudo-boolean function

$$\min_y \sum_{y_i \in \mathcal{C}(D)} \hat{k}_R^2(y_i)$$

$$\min_y \sum_{p \in \mathcal{C}(D)} \left((1/2 + |F_r(p)| - c_2) \cdot \sum_{y_i \in Y_r(p)} y_i + \sum_{y_i, y_j \in Y_r(p); i < j} y_i y_j \right)$$

$$\frac{\partial^2 \hat{E}}{\partial y_i \partial y_j} \geq 0, \quad \forall i \neq j$$

Supermodular
energy

Quadratic pseudo-boolean function

Quadratic pseudo-boolean function

QPBOP: Returns partial solution. Some pixels are not labeled.

Quadratic pseudo-boolean function

QPBOF: Returns partial solution. Some pixels are not labeled.

QPBOI: Improves a partial solution value and returns a full labeling. Partial optimality property is loss.

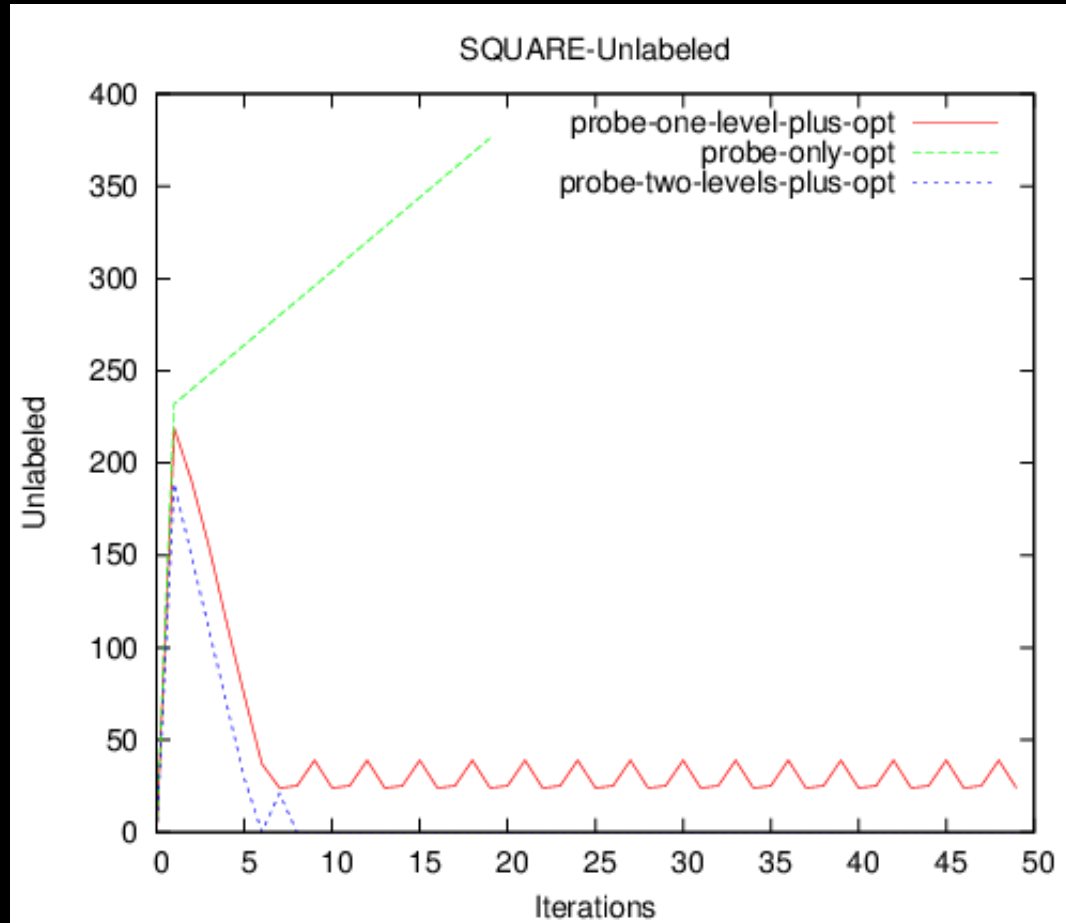
Quadratic pseudo-boolean function

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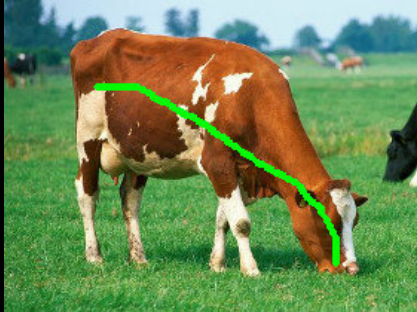
If energy is submodular, **QPBOF** labels all variables.

Unlabeled pixels

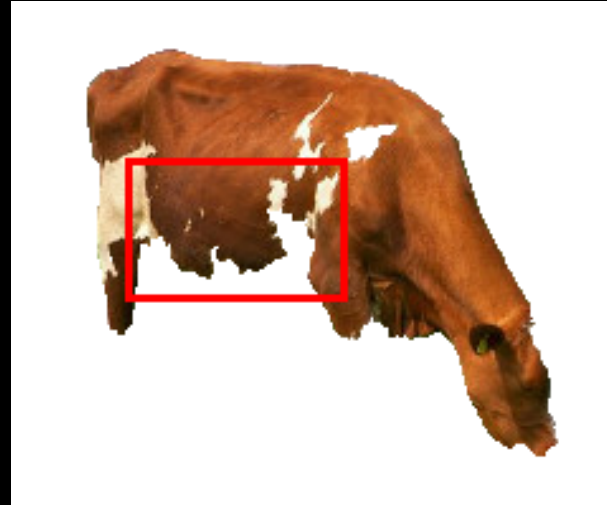
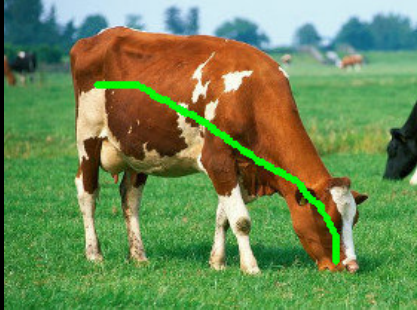


Segmentation post-processing

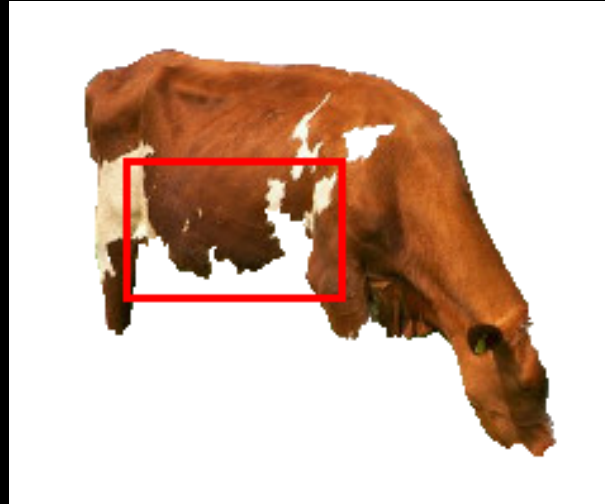
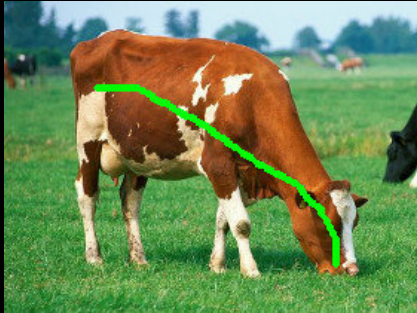
Segmentation post-processing



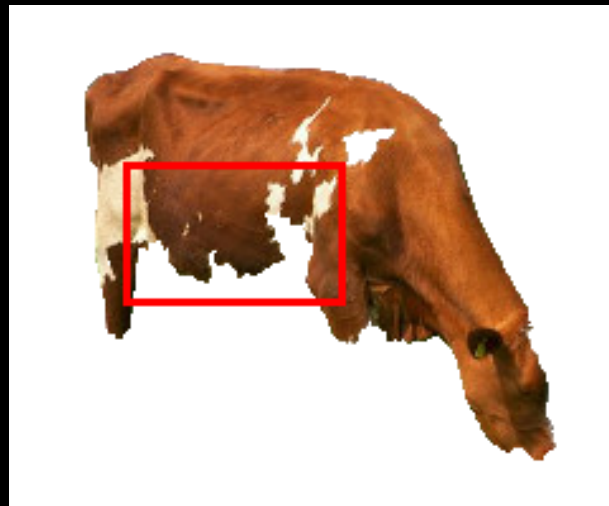
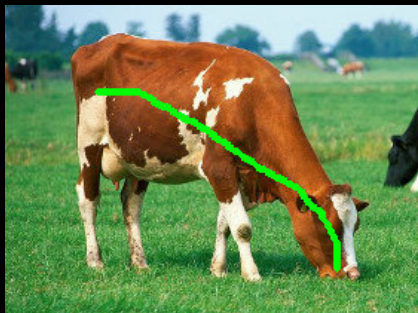
Segmentation post-processing



Segmentation post-processing



Segmentation post-processing



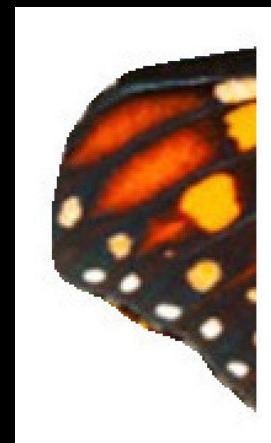
Segmentation post-processing



Segmentation post-processing



Segmentation post-processing





Model summary

Model summary



Flow based on a multigrid convergent estimator of curvature





Model summary

-  Flow based on a multigrid convergent estimator of curvature
-  Post-processing step in image segmentation

Model summary

- ⊕ Flow based on a multigrid convergent estimator of curvature
- ⊕ Post-processing step in image segmentation
- ⊕ Works well with extra terms (data fidelity, perimeter)

Model summary

-  Flow based on a multigrid convergent estimator of curvature
-  Post-processing step in image segmentation
-  Works well with extra terms (data fidelity, perimeter)
-  Too local. Completion property is not recovered

Digital Curvature Evolution Model for Image Segmentation

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Thank you for your
attention!