Extracting Autofluorescence from Diffuse Optical Images

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Problem Definition

- Company: ART Advanced Research Technologies Inc.
- Develop a tomography algorithm for small animal fluorescence imaging
  - Laser illumination (NIR-visible)
  - Localization of molecules
  - Estimation of molecule concentration

Challenges

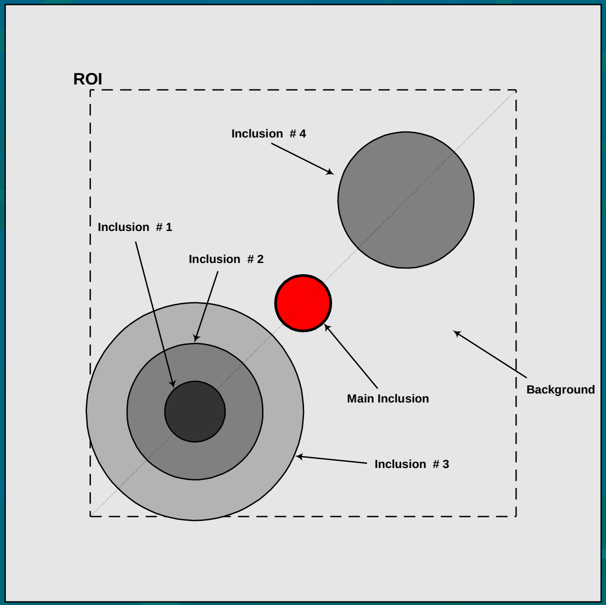
- **Non-trivial small animal boundaries**
  (non-contact illumination / collection)
- **Highly heterogeneous samples**
  (*Optical properties*)
- **Non-specific fluorescence background**
  (e.g., tissue auto-fluorescence)
- **Ill-posed nature of diffuse optical problems**

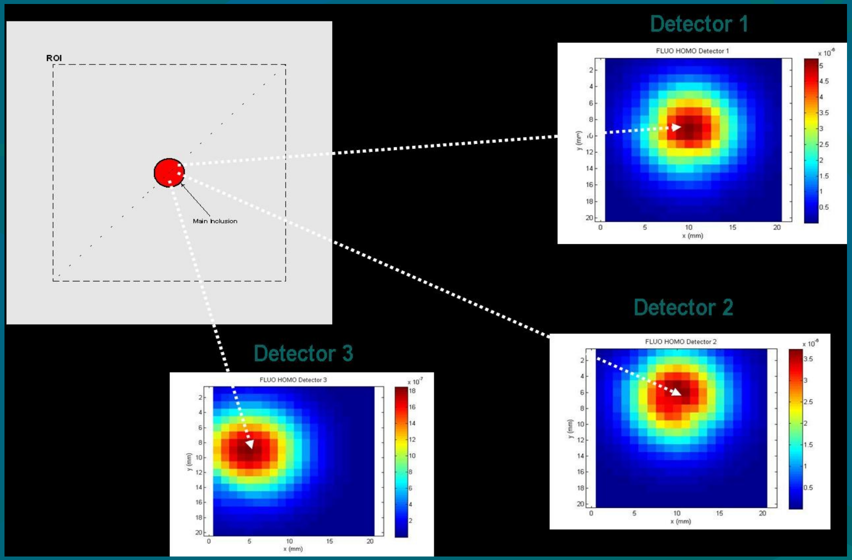
Objectives

- Analyze optical images
- Identify local structures
- Extract autofluorescence from images
- Data: synthetic data

  in vivo data

Synthetic Data

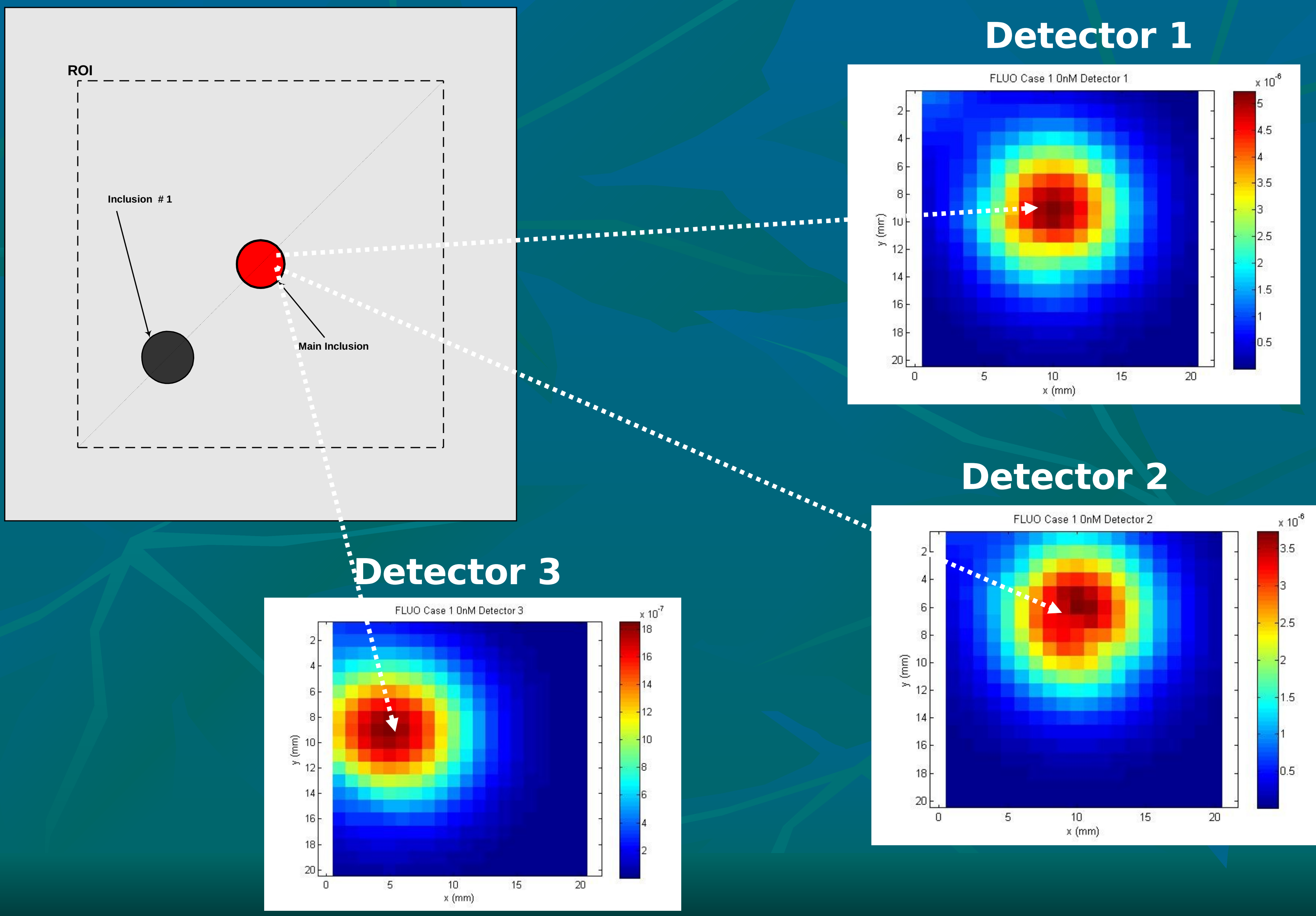




- Fluorescent inclusions
- Fluorescent background

Homogeneous **Baseline Images**

Simulated data: Case 1



Approaches

- Localization of inclusions
  - Wavelet Transform
  - PCA (Principle Component Analysis)
  - Cross-correlation
- Shape fitting and removal of the identified objects
  - Median profile
  - Model fitting

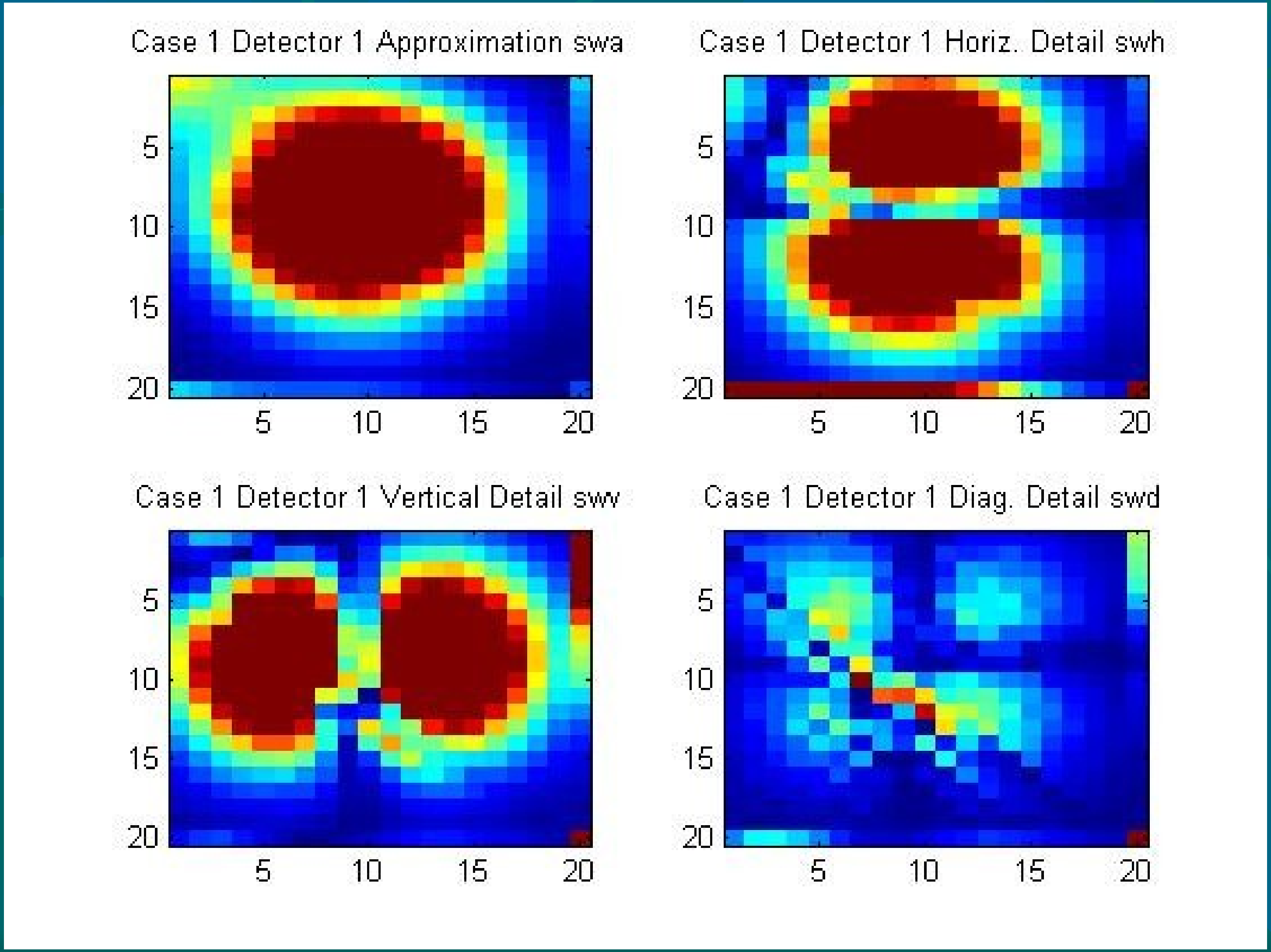
2D Stationary Wavelet Transform

- Perform multi-level wavelets decomposition on image X:

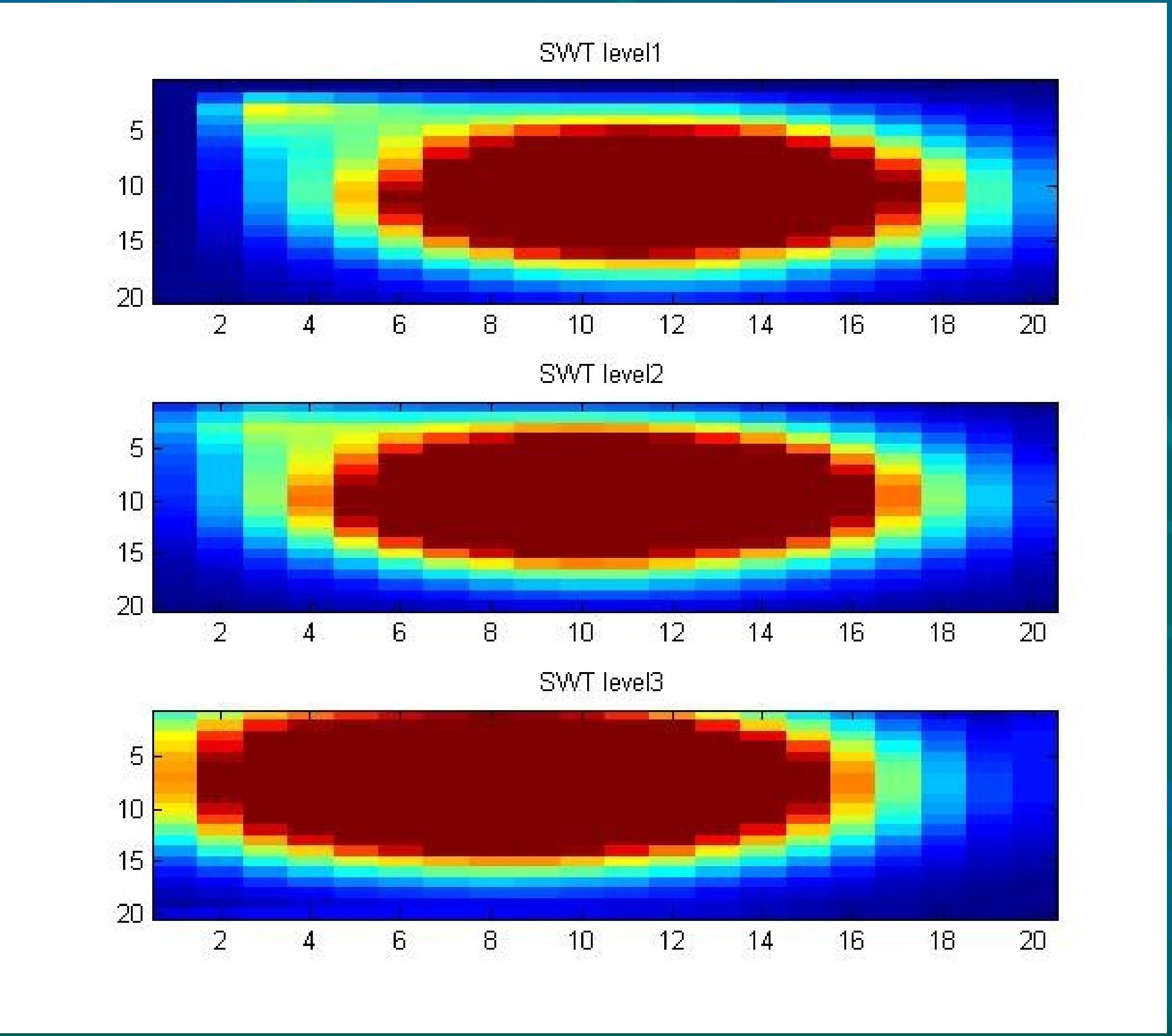
  [swa,swh,swv,swd] = swt2(X, n,'db1')

  - n: level number
  - ‘db1’: a specific orthogonal wavelet
  - swa: coefficients of the image approximation
  - swh: coefficients of horizontal details
  - swv: coefficients of vertical details
  - swd: coefficients of diagonal details

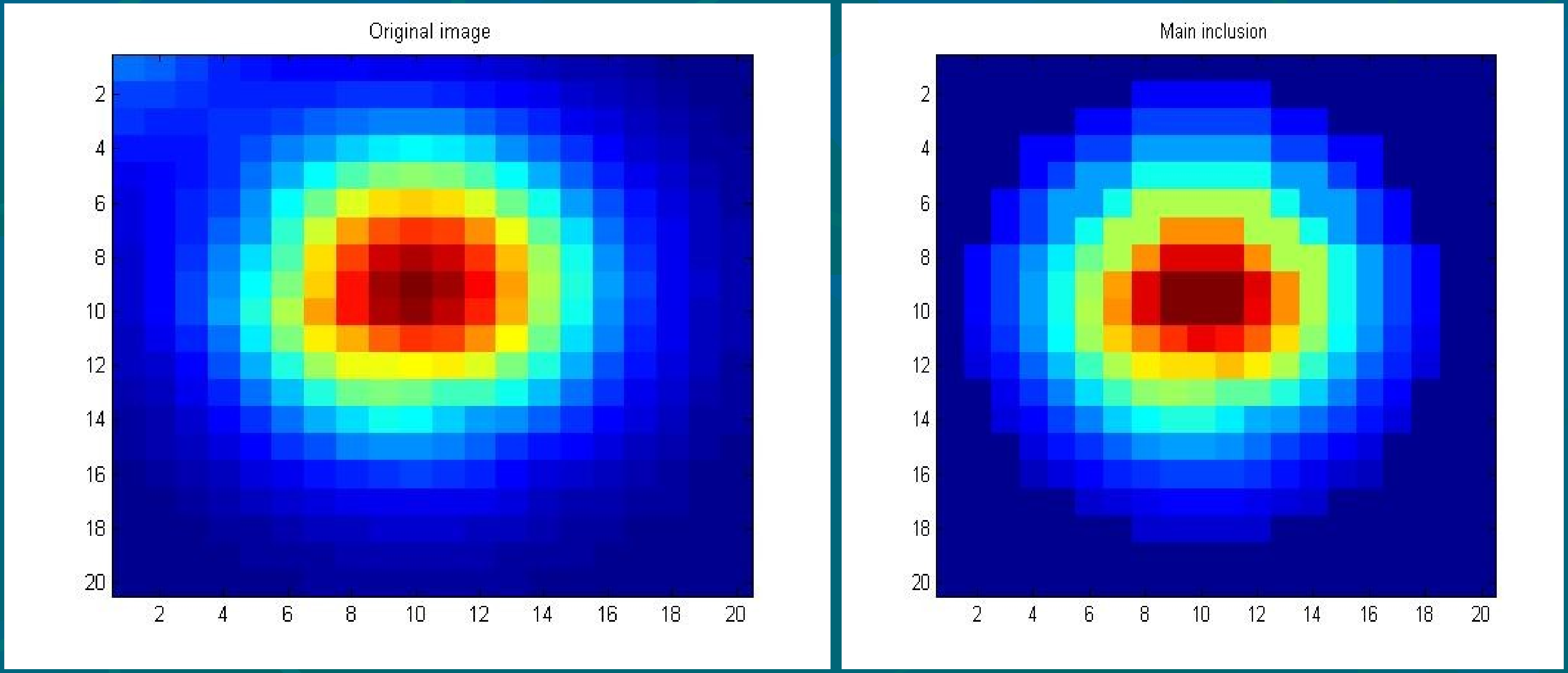
Wavelet Decomposition



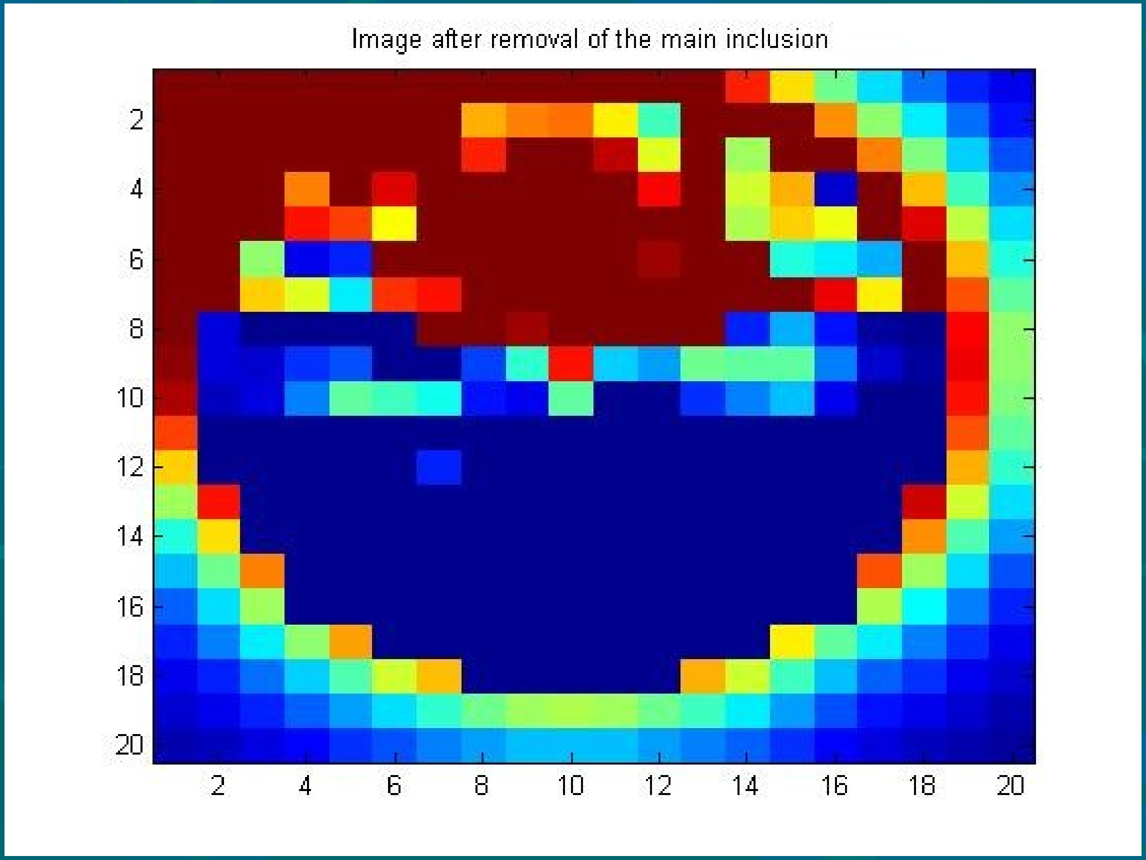
Localize the Main Structure



Extracting the Main Inclusion



After Extracting

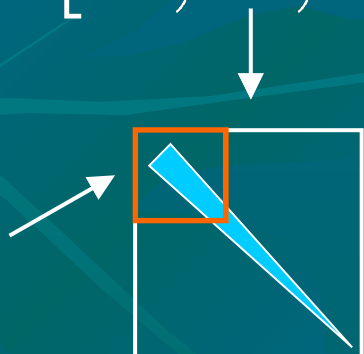


Principal Component Analysis

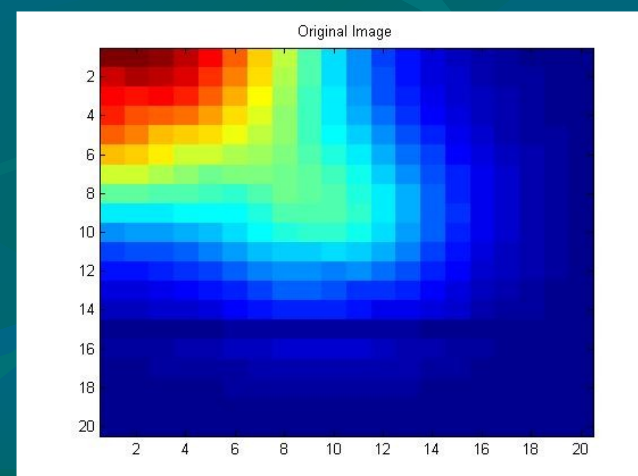
- Enhances visibility of the features: can handle irregular shapes
- Singular Value Decomposition (SVD)

$$[U, S, V] = svd(A)$$

S_0



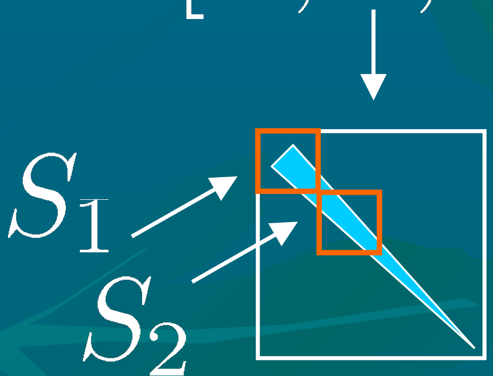
$$A_0 = U \cdot S_0 \cdot V'$$



PCA II

- Choose first and second eigenvalues

$$[U, S, V] = svd(A)$$



$$A_1 = U \cdot S_1 \cdot V'$$

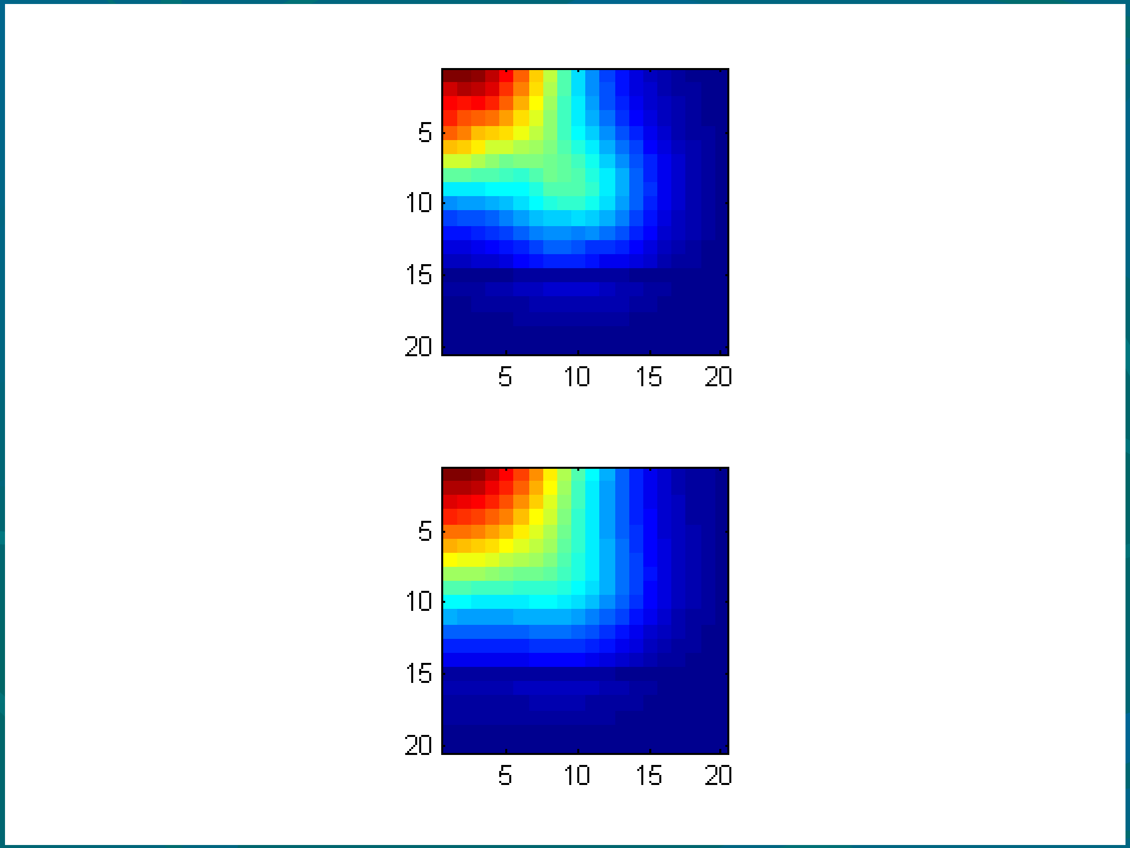
$$A_2 = U \cdot S_2 \cdot V'$$

$$A = \alpha \cdot A_1 + A_2$$

PCA Demo: Synthetic Image

Initial Image

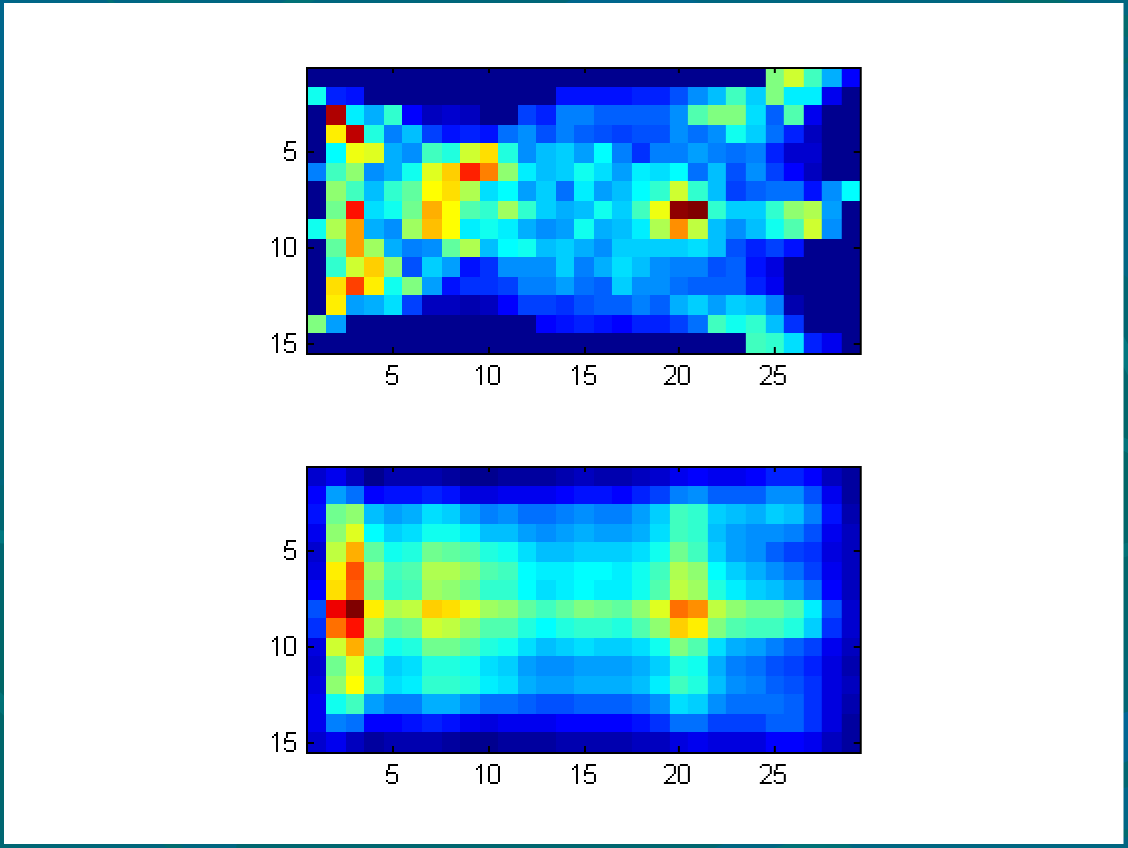
Components



PCA Demo: Mouse

Initial Image

Components

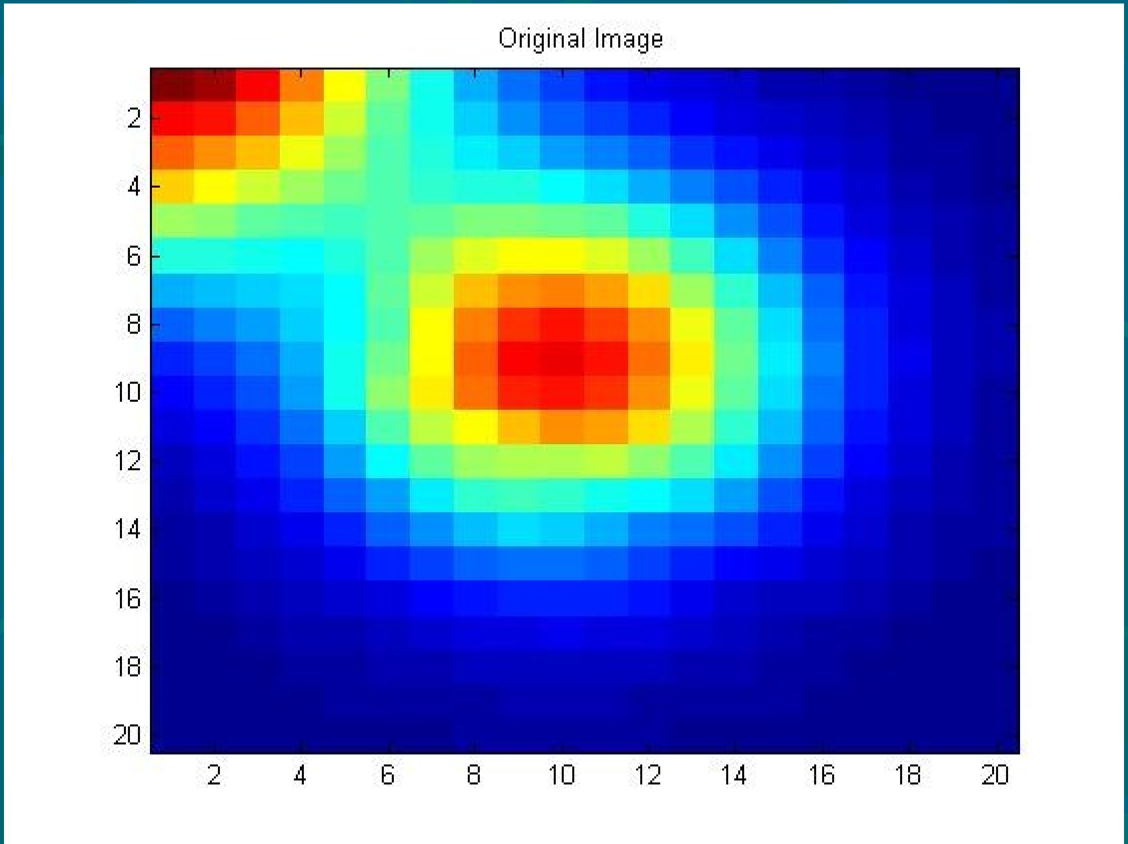


Algorithm

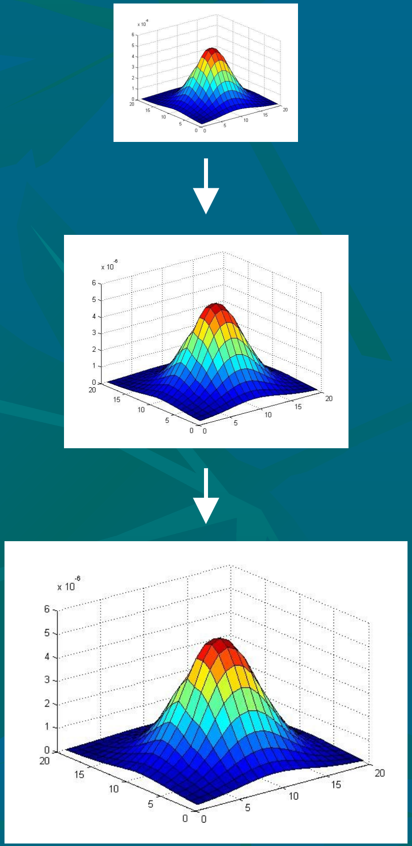
- Locate the part of the image conforming the most to the template
  - Cross-correlation
- Analyze the shape and size and
- Remove the bump from the image
  - Model fitting

Localization: Cross-Correlation

Original Image



Templates



Cross-Correlation

- For each size of the template compute cross-correlation matrix
- For every size, choose the location of maximum correlation
- Find the location which conformed to the most sizes of the templates or the one containing the brightest pixels

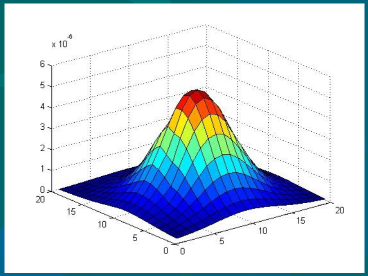
Model Fitting

- Fit image data $\phi_{x,y}$ to the model

$$min_p \ \ \| f_p(x,y) - \phi_{x,y} \|^2$$

- Model:
  - Gaussian

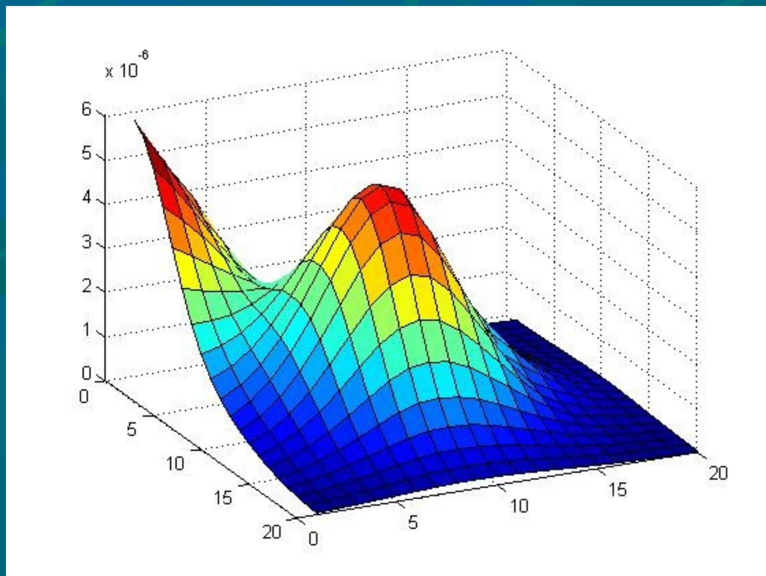
$$f_p(x,y) = v_0 + v_1 e^{-s(x,y)}$$



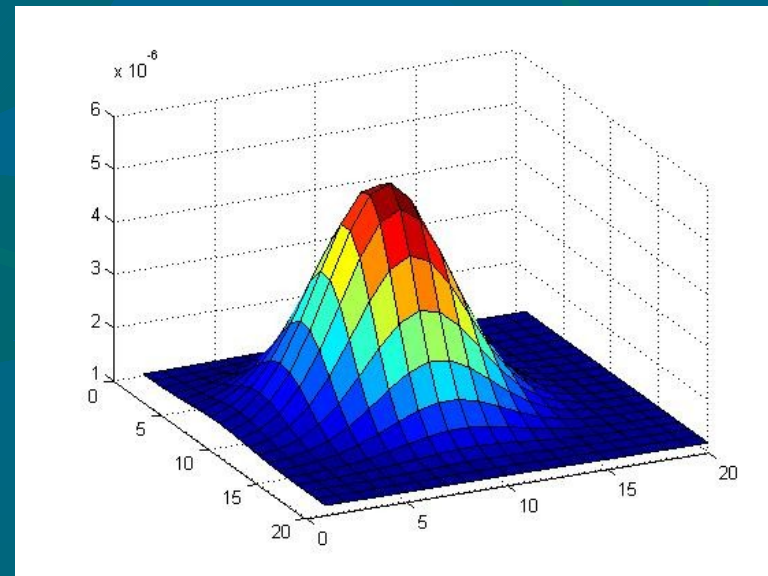
where

$$s(x,y) = a_1 x^2 + a_2 xy + a_3 y^2$$

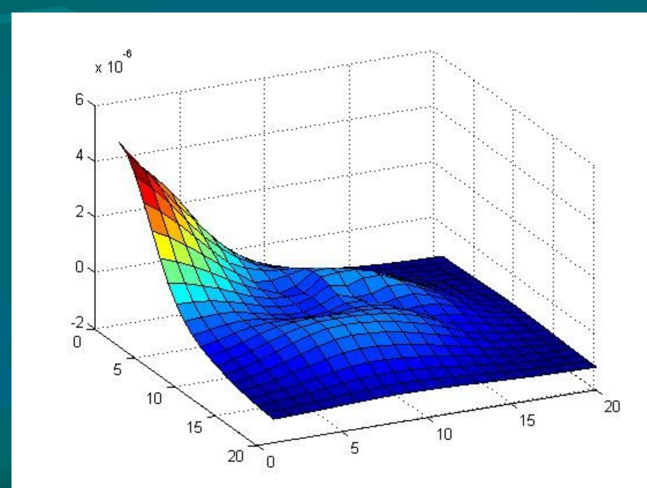
Bump Fitting and Removal



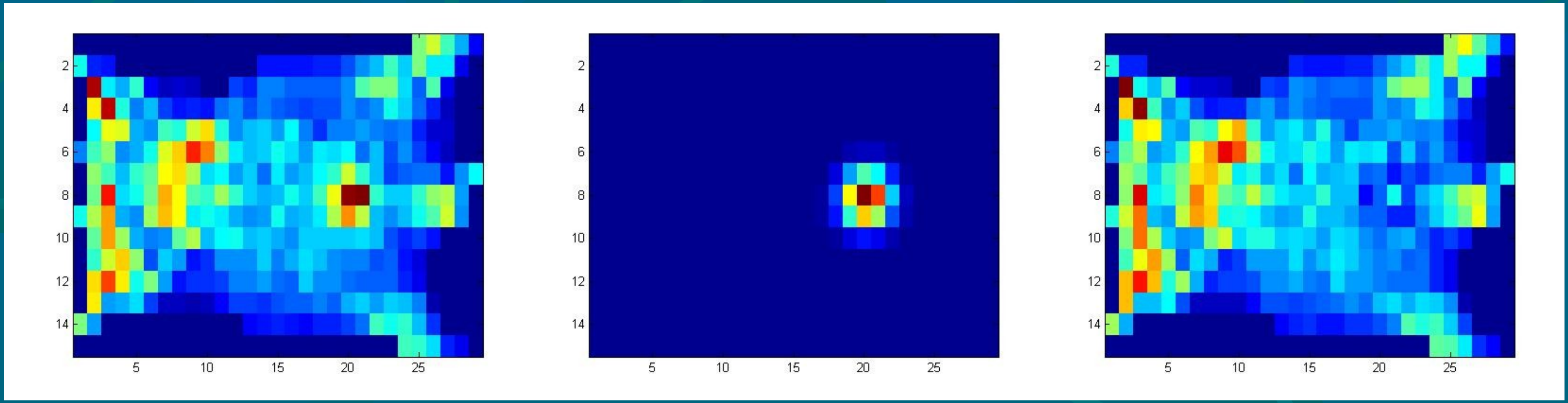
Data

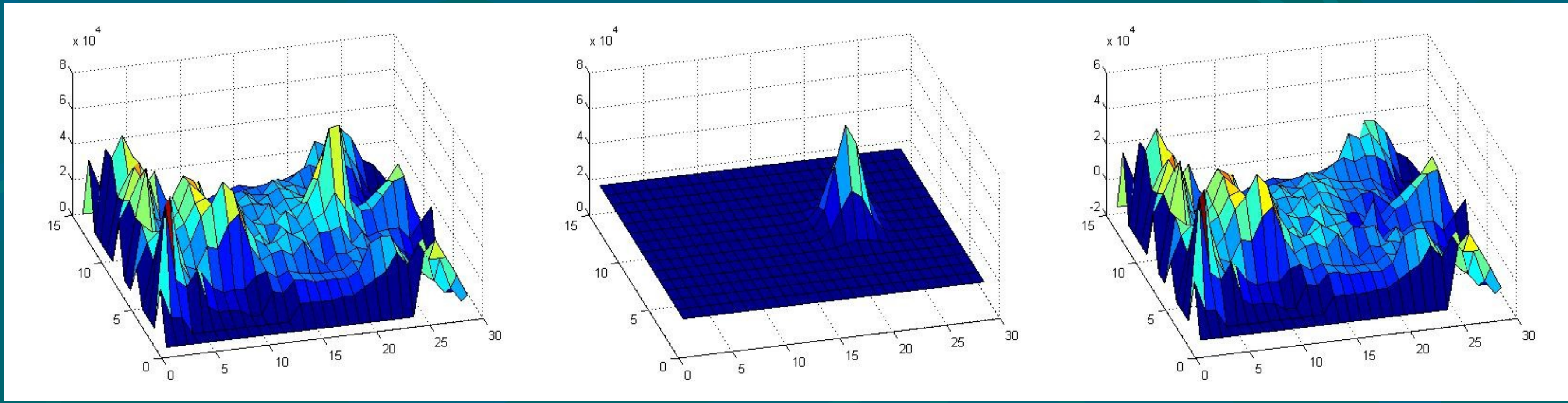


Model

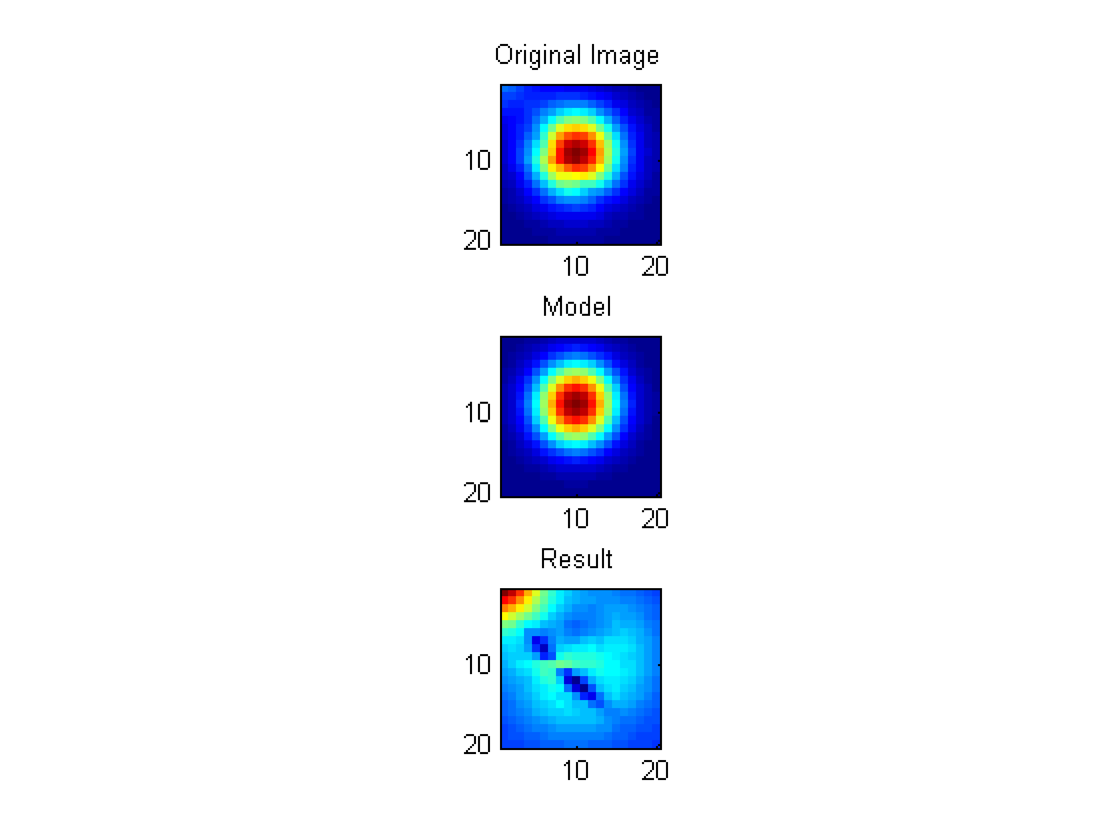


Bump Fitting and Removal II

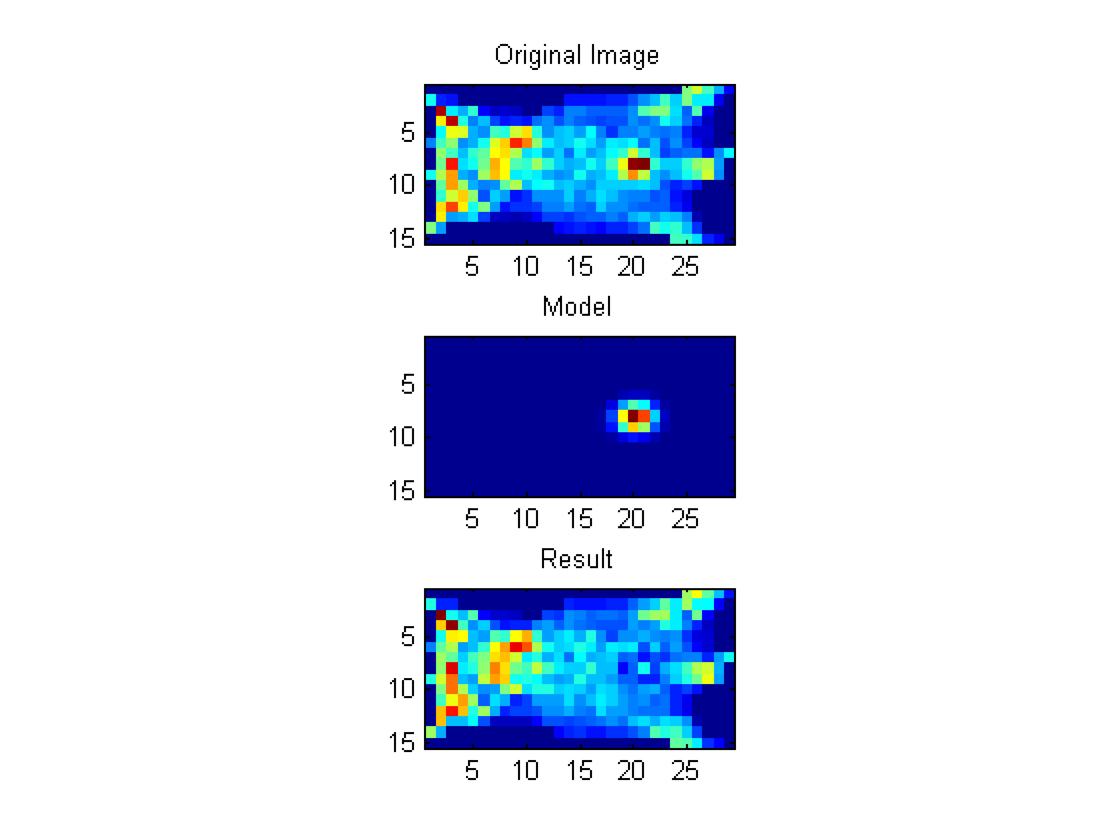




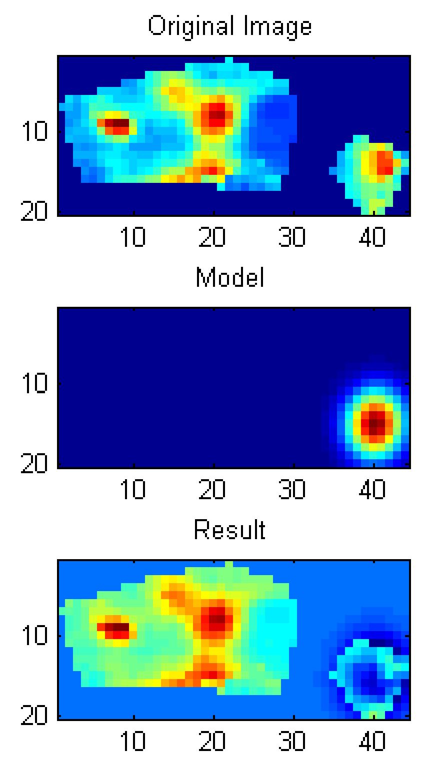
Algorithm Dynamics: Synthetic Data



Algorithm Dynamics: Mouse



Algorithm Dynamics: Mouse II



Future Work

- Test the algorithm, make more robust
- Analyze the model parameters resulting from the fitting procedure to separate targets from autofluorescent object
- Test on more data