Lecture 12: Texture

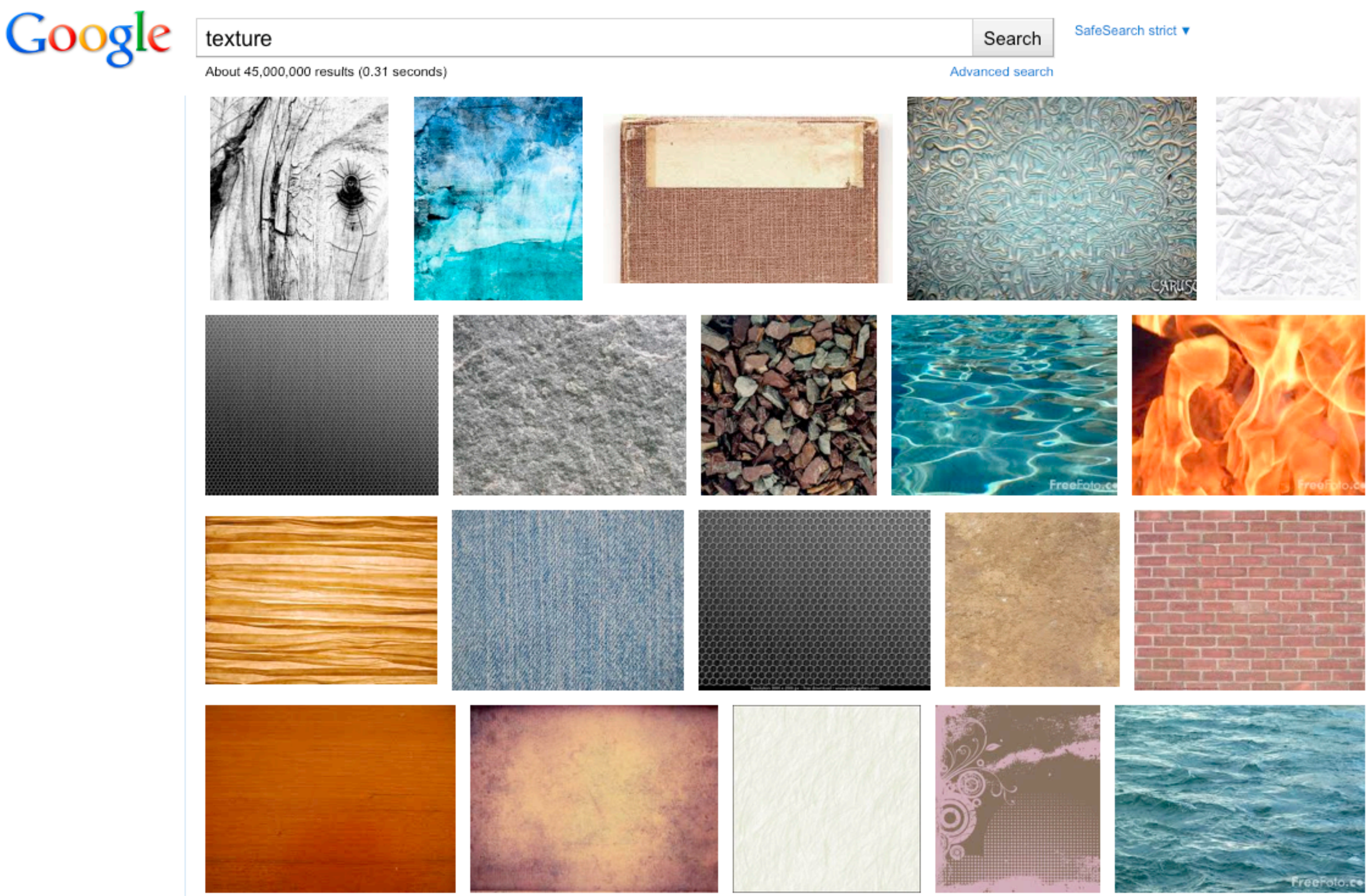
COS 429: Computer Vision

PRINCETON UNIVERSITY

Acknowledgment: slides from Antonio Torralba, Kristen Grauman, Jitendra Malik, Alyosha Efros, Tom Funkhouser, Szymon Rusinkiewicz

Texture

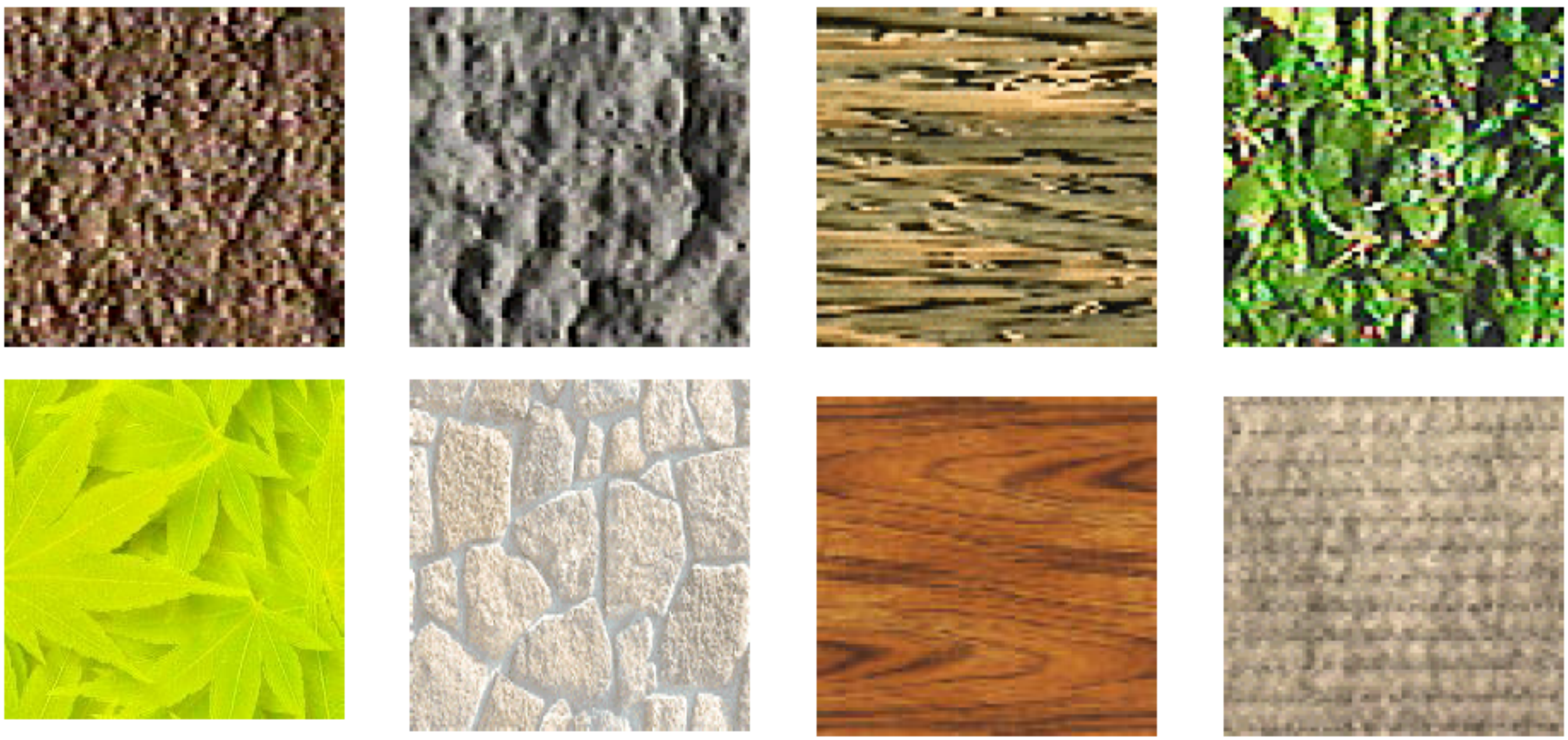
What is a texture?



Torralba

Texture

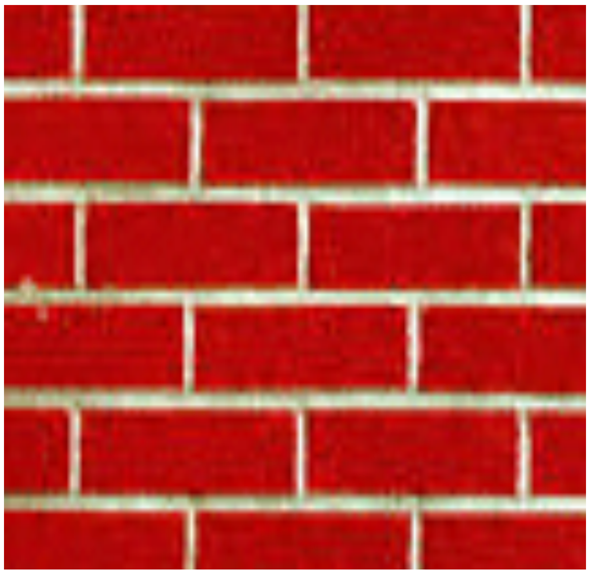
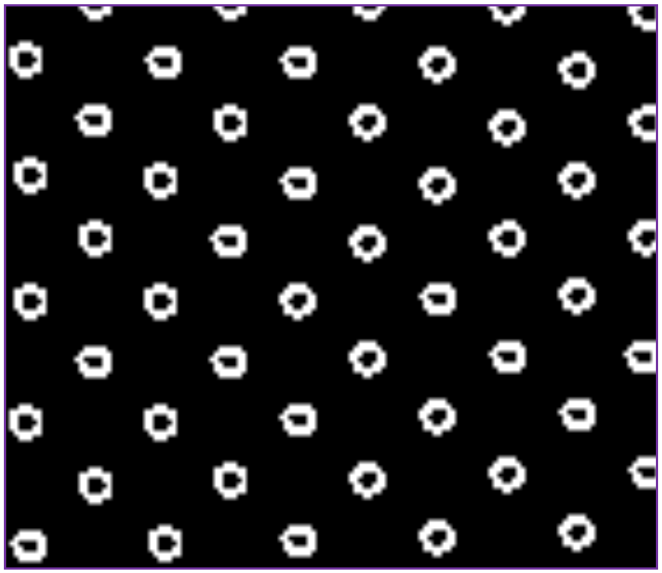
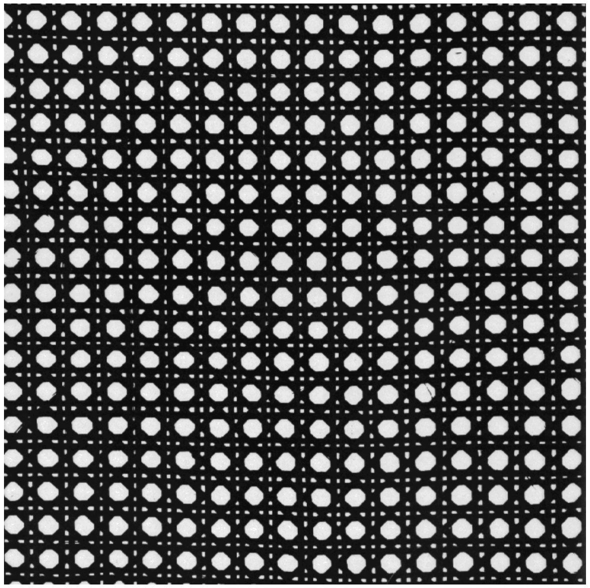
What is a texture?



Torralba

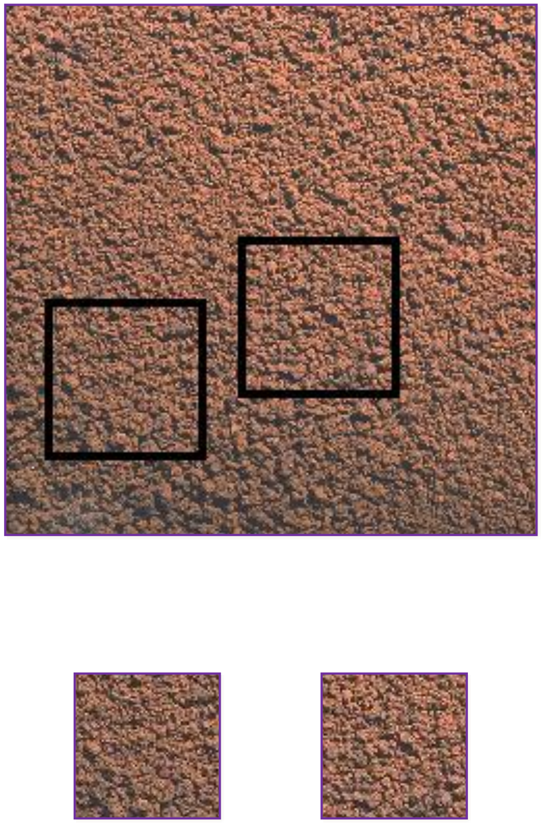
Texture

What is a texture?

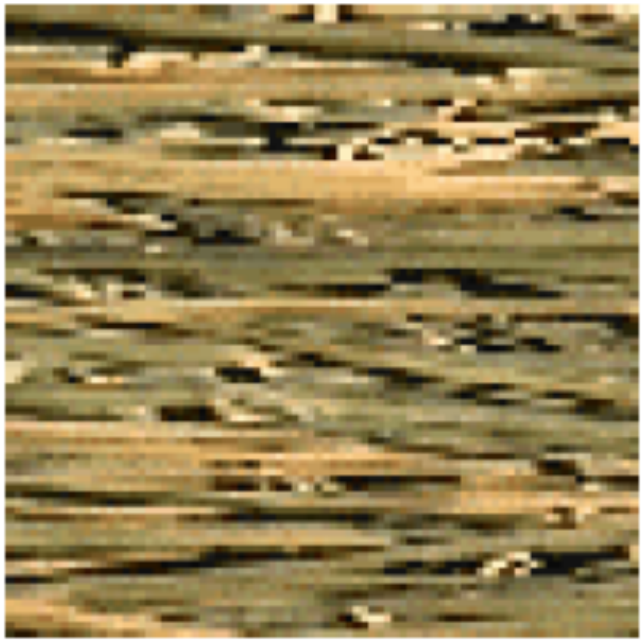
Texture

- Texture: stochastic pattern that is stationary ("looks the same" at all locations)
- May be structured or random



Wei & Levoy

Texture



Stochastic Stationary

Texture

Stochastic   Stationary

Goal

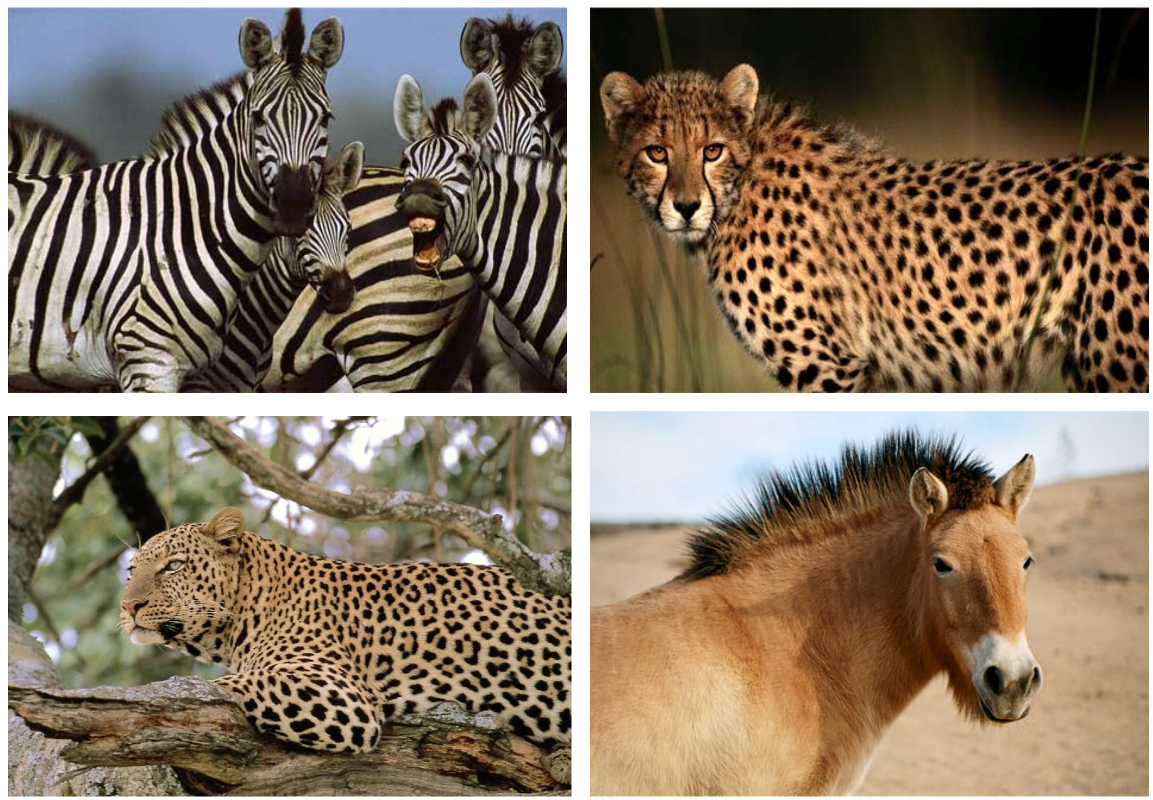
- Computational representation of texture
  - Textures generated by same stationary stochastic process have same representation
  - Perceptually similar textures have similar representations

5, 7, 34, 2, 199, 12

Hypothetical texture representation

Applications

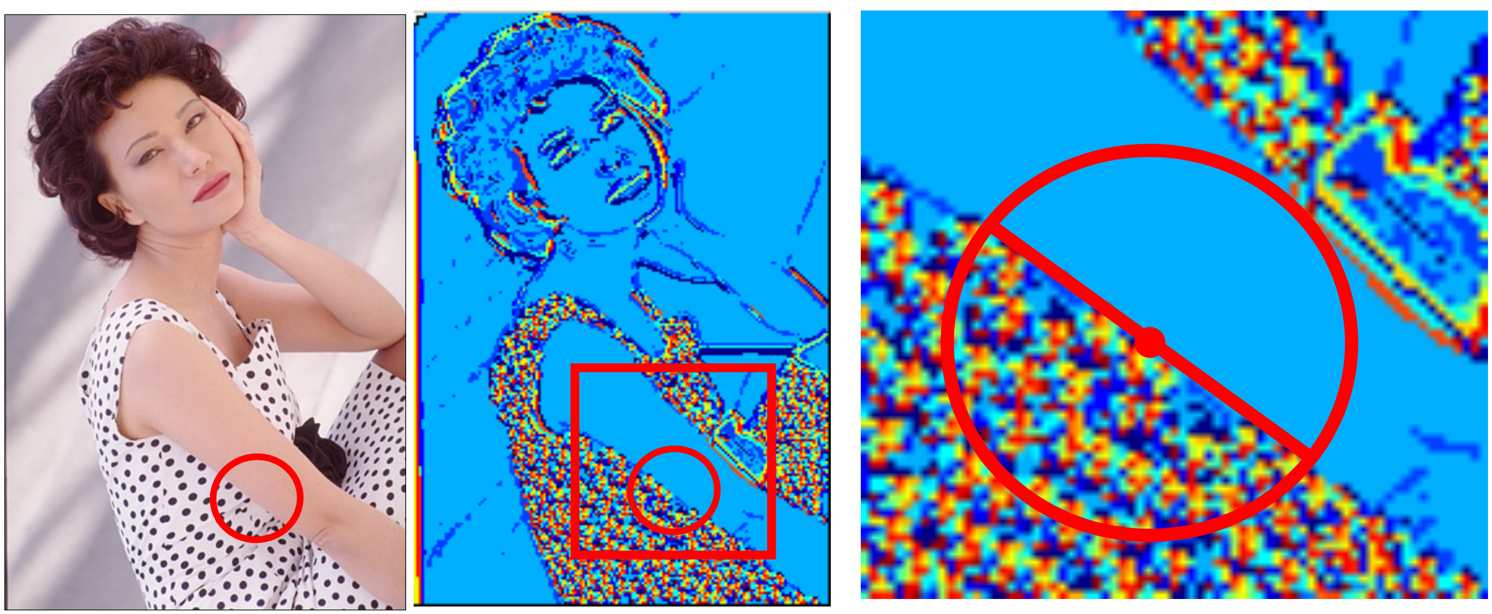
- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



http://animals.nationalgeographic.com/

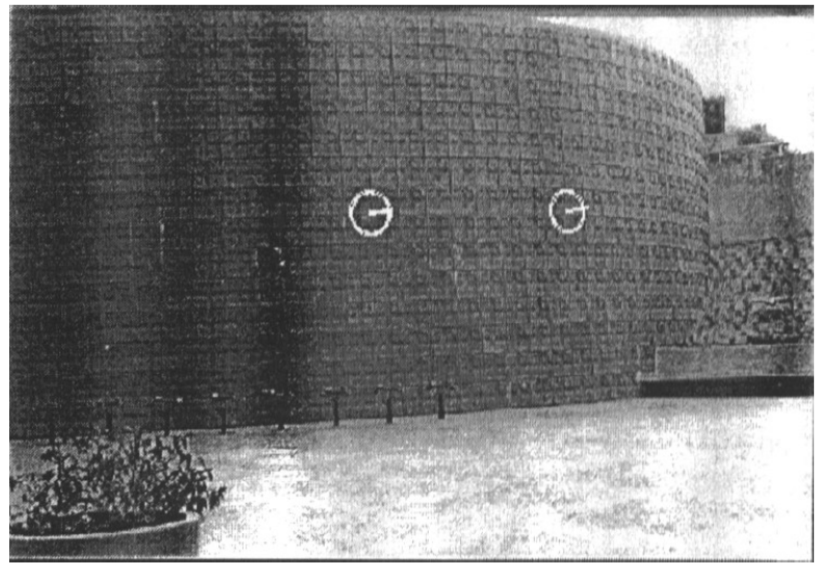
Applications

- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



Applications

- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



Grauman

Applications

- Segmentation
- 3D Reconstruction
- Classification
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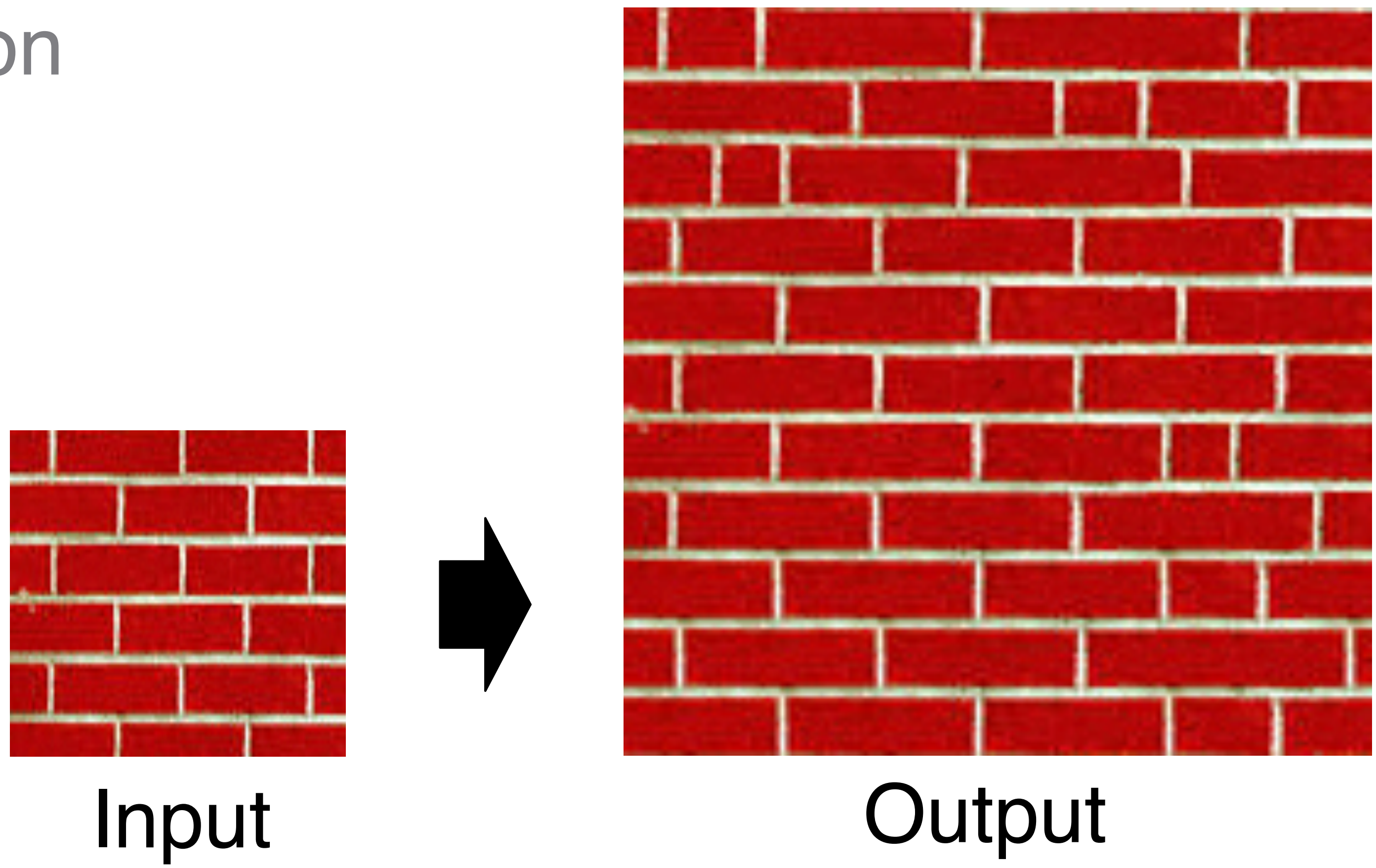
Applications

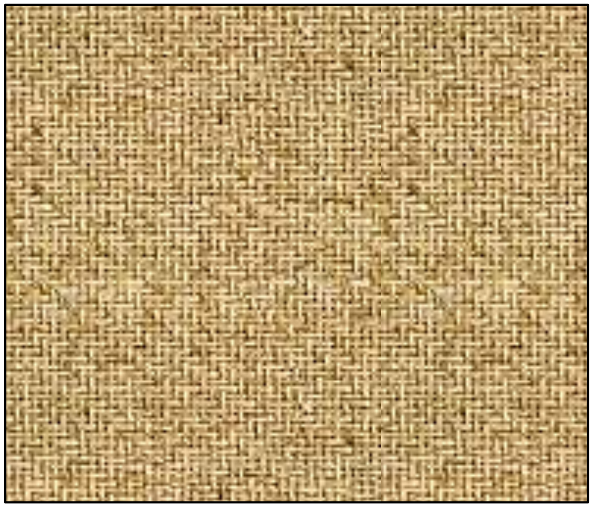
- Segmentation
- 3D Reconstruction
- Classification
- Synthesis



Efros

Texture Representation?

- What makes a good texture representation?
  - Textures generated by same stationary stochastic process have same representation
  - Perceptually similar textures have similar representations

Statistics of filter banks

Filter-Based Texture Representation

- Research suggests that the human visual system performs local spatial frequency analysis (Gabor filters)

J. J. Kulikowski, S. Marcelja, and P. Bishop.
Theory of spatial position and spatial frequency relations in the receptive fields of simple cells in the visual cortex.
Biol. Cybern, 43:187-198, 1982.

Texture Representation

- Analyze textures based on the responses of linear filters
  - Use filters that look like patterns (spots, edges, bars, …)
  - Compute magnitudes of filter responses
- Represent textures with statistics of filter responses within local windows
  - Histogram of feature responses for all pixels in window

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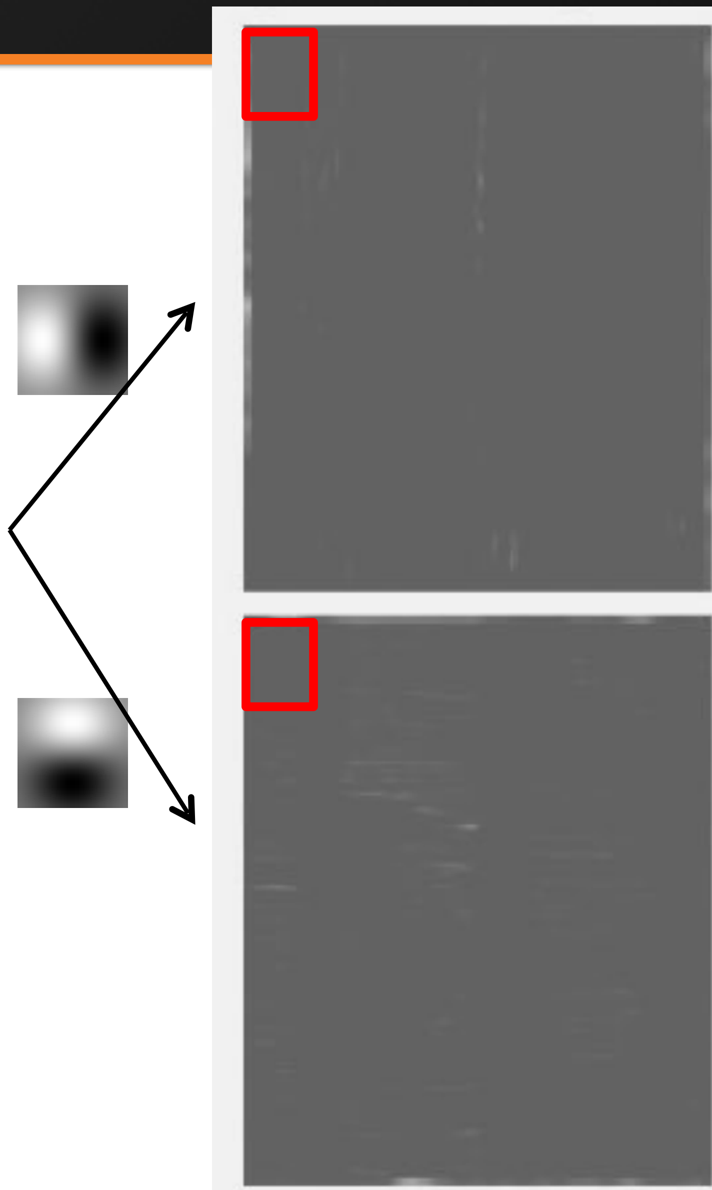
Texture Representation Example

original image



derivative filter responses, squared

	mean d/dx value	**mean d/dy value**
Win. #1	4	10

statistics to summarize patterns in small windows

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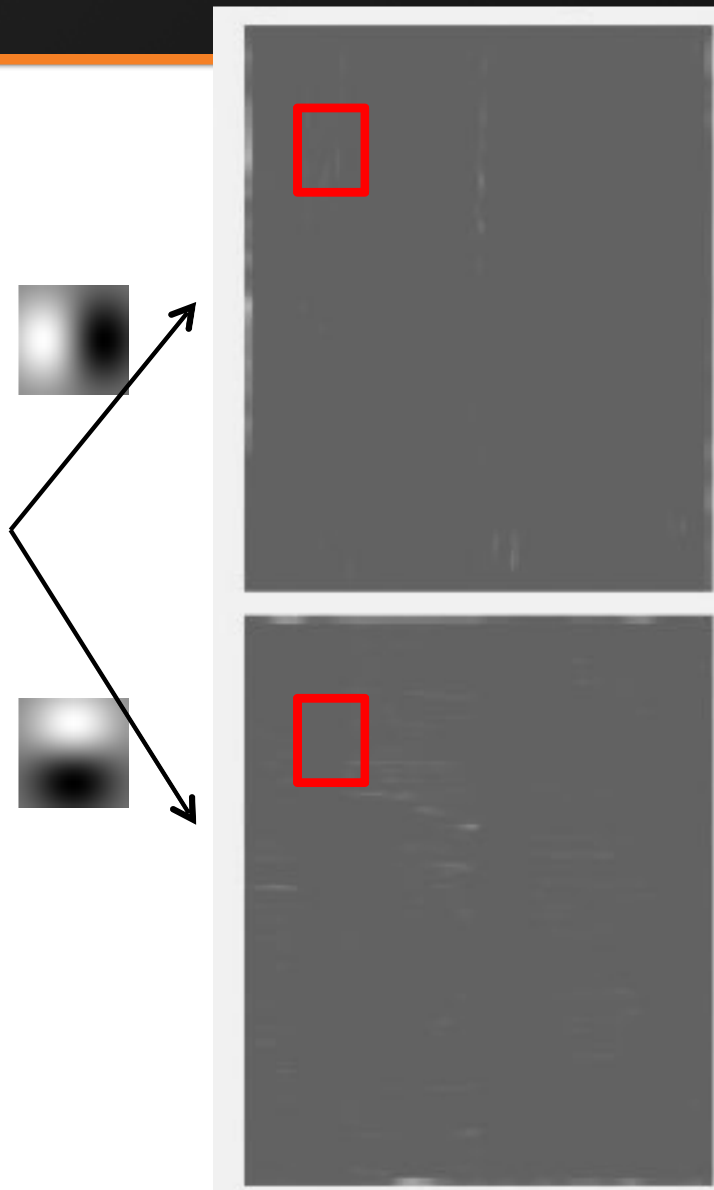
Texture Representation Example

original image



derivative filter responses, squared

	mean d/dx value	**mean d/dy value**
Win. #1	4	10
Win.#2	18	7

statistics to summarize patterns in small windows

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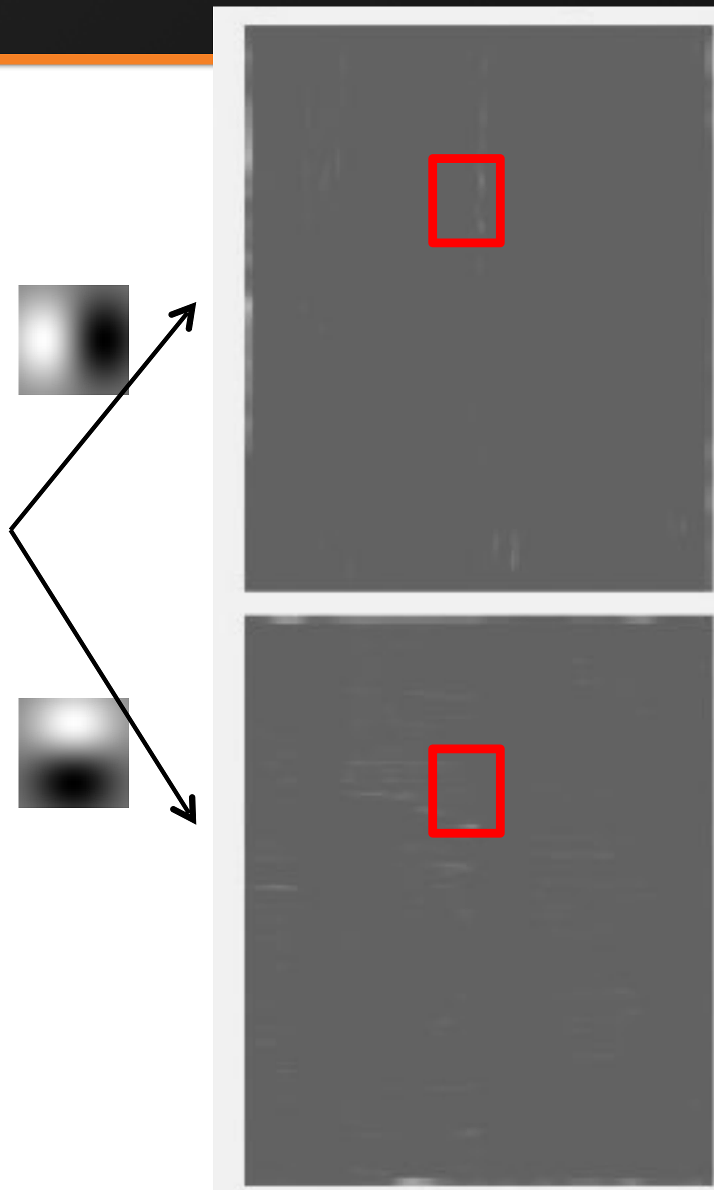
Texture Representation Example

original image



derivative filter responses, squared

	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2	18	7
⋮		
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

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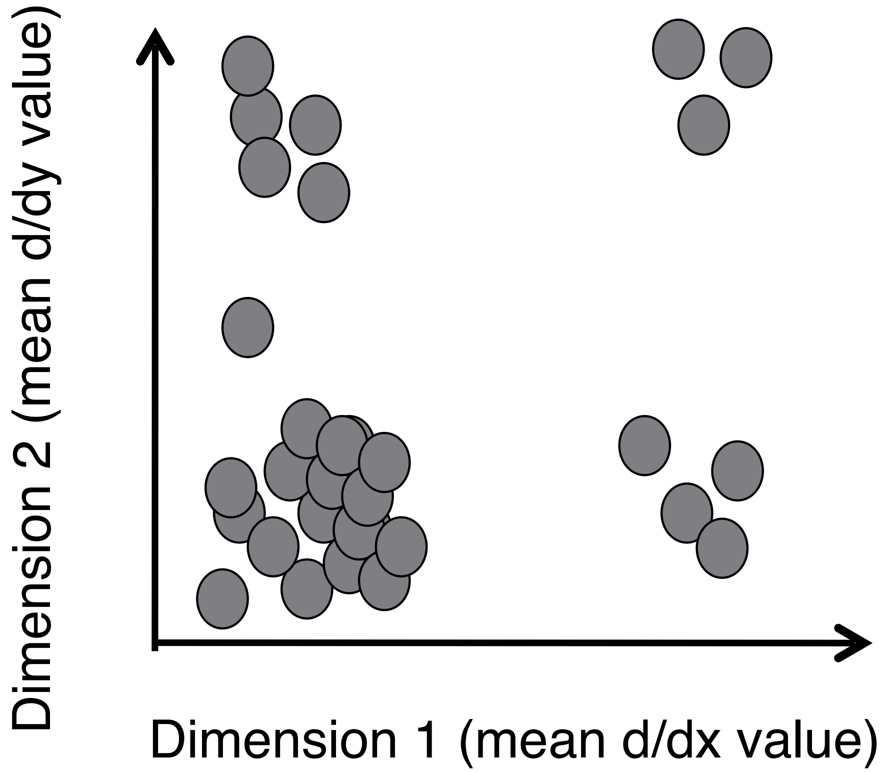
Texture Representation Example



	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2	18	7
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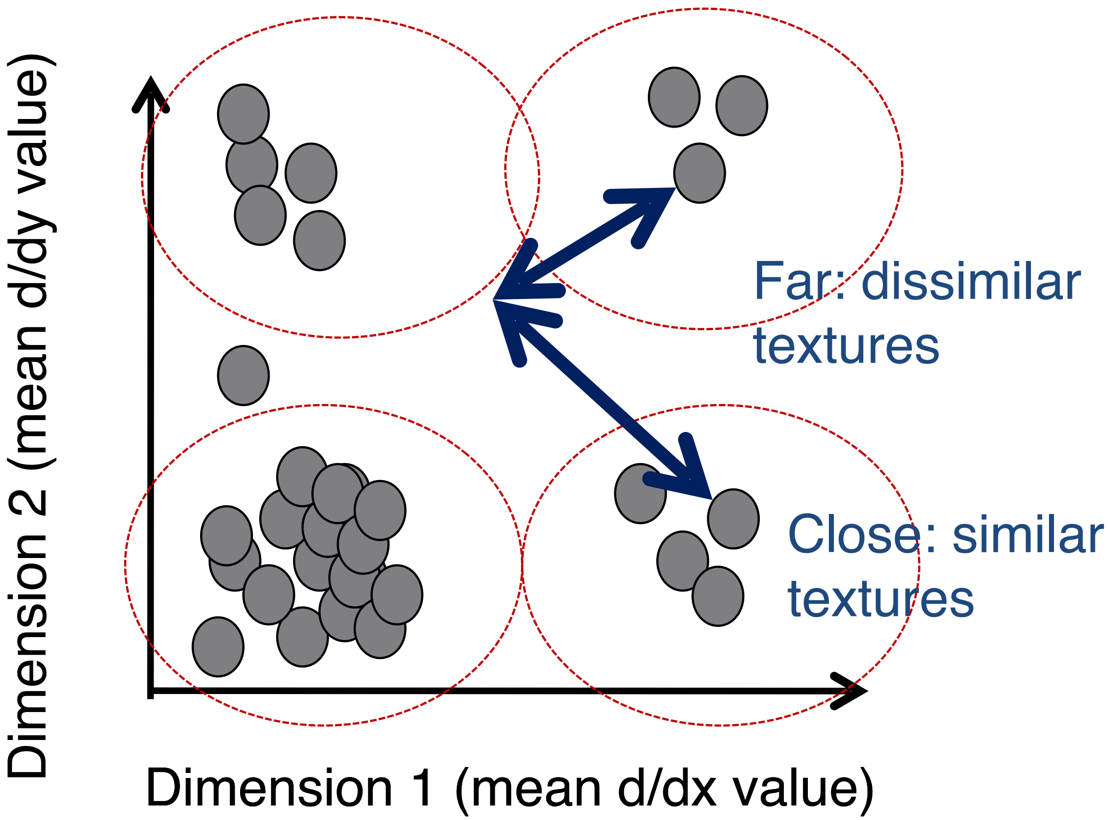
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

Texture Representation Example



	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2	18	7
⋮		
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

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Filter Banks

- Previous example used two filters, resulting in 2-dimensional feature vector
  - x and y derivatives revealed local structure
- Filter bank: many filters
  - Higher-dimensional feature space
  - Distance still related to similarity of local structure

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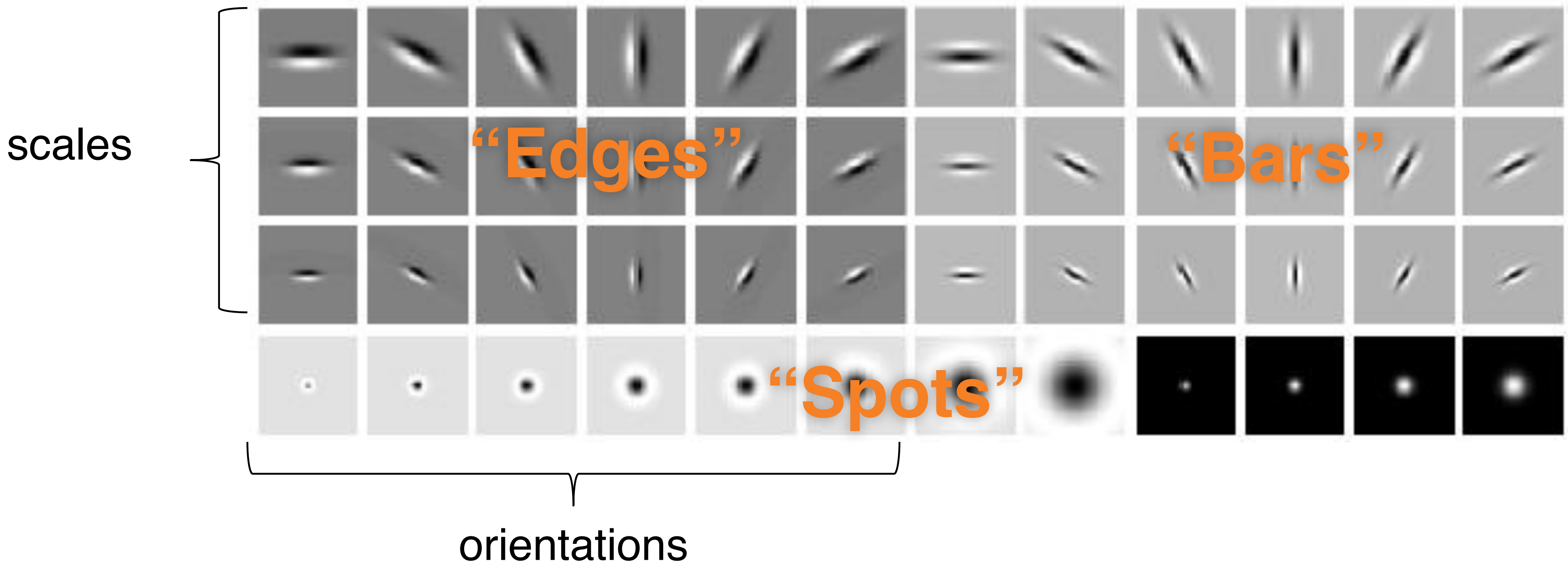
Filter banks



- What filters to put in the bank?
  - Combination of different scales, orientations, patterns

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Image from http://www.texasexplorer.com/austincap2.jpg

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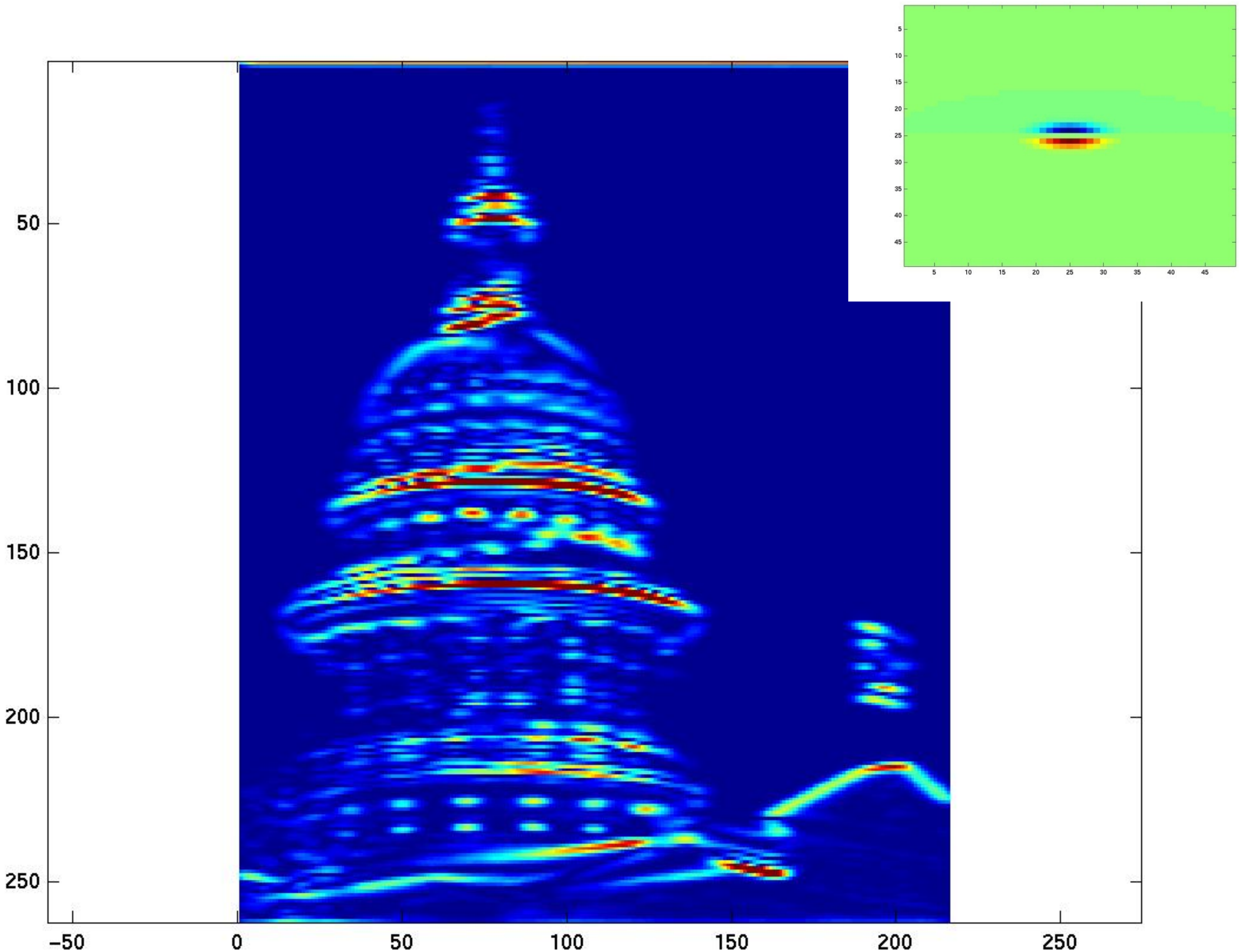
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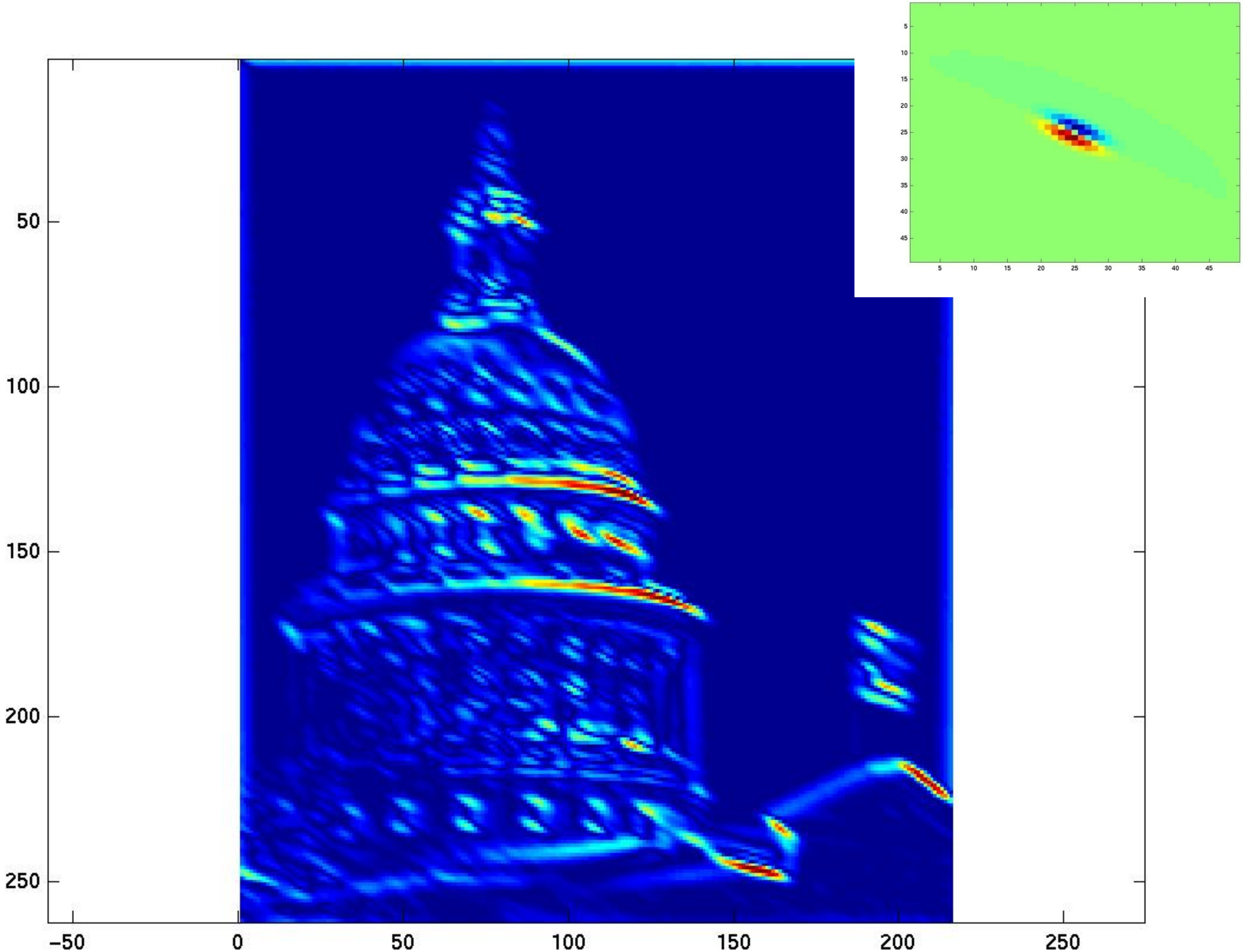

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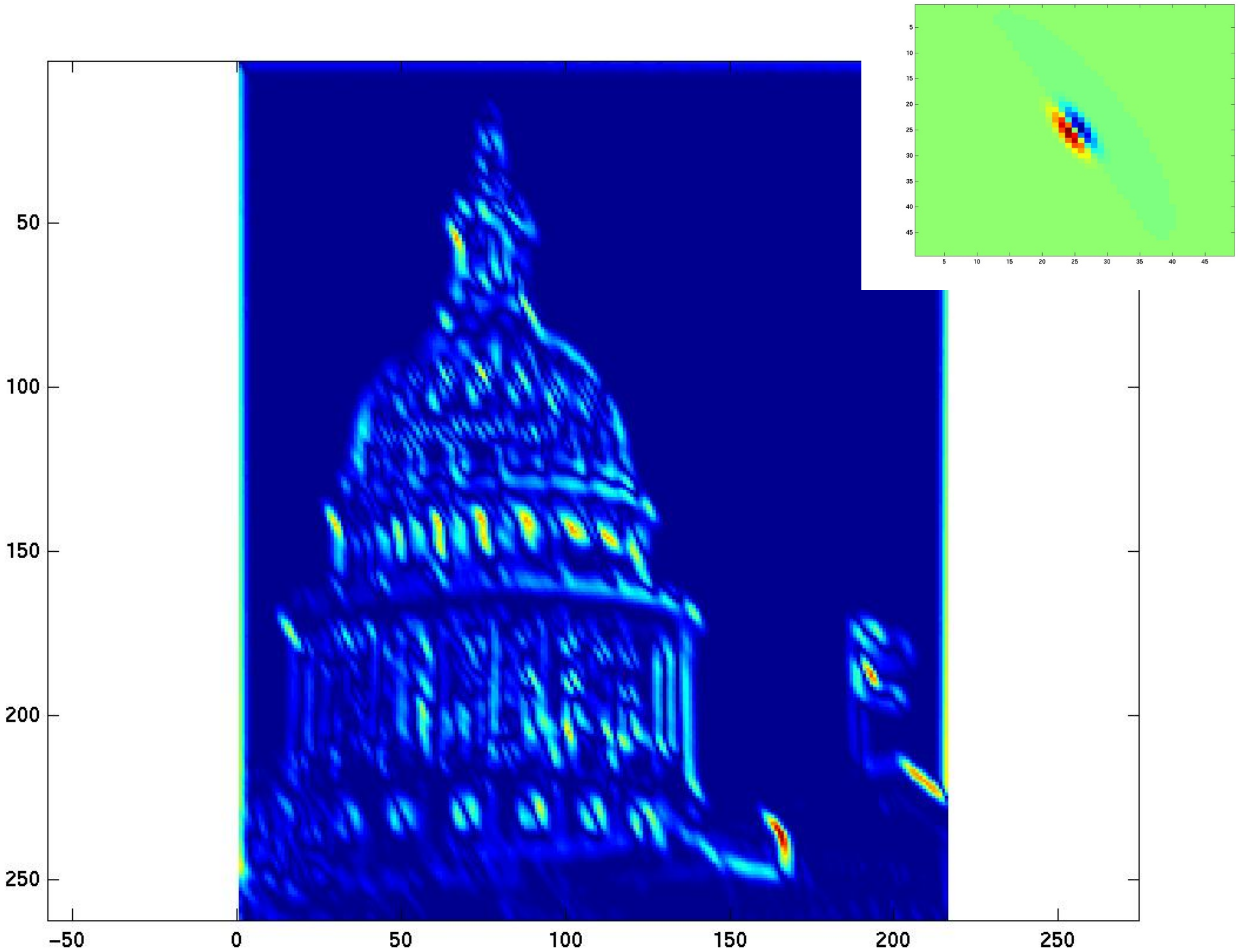

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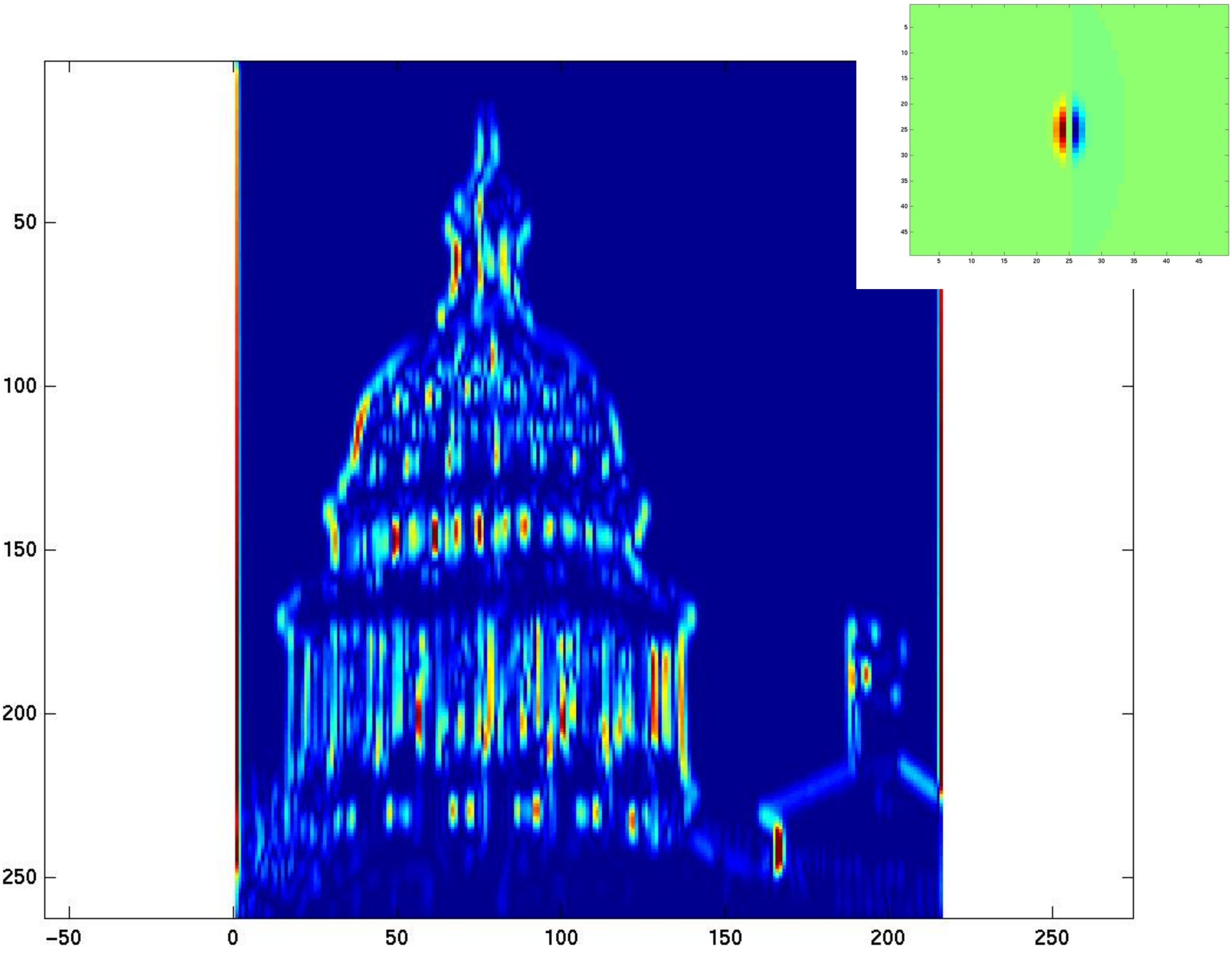

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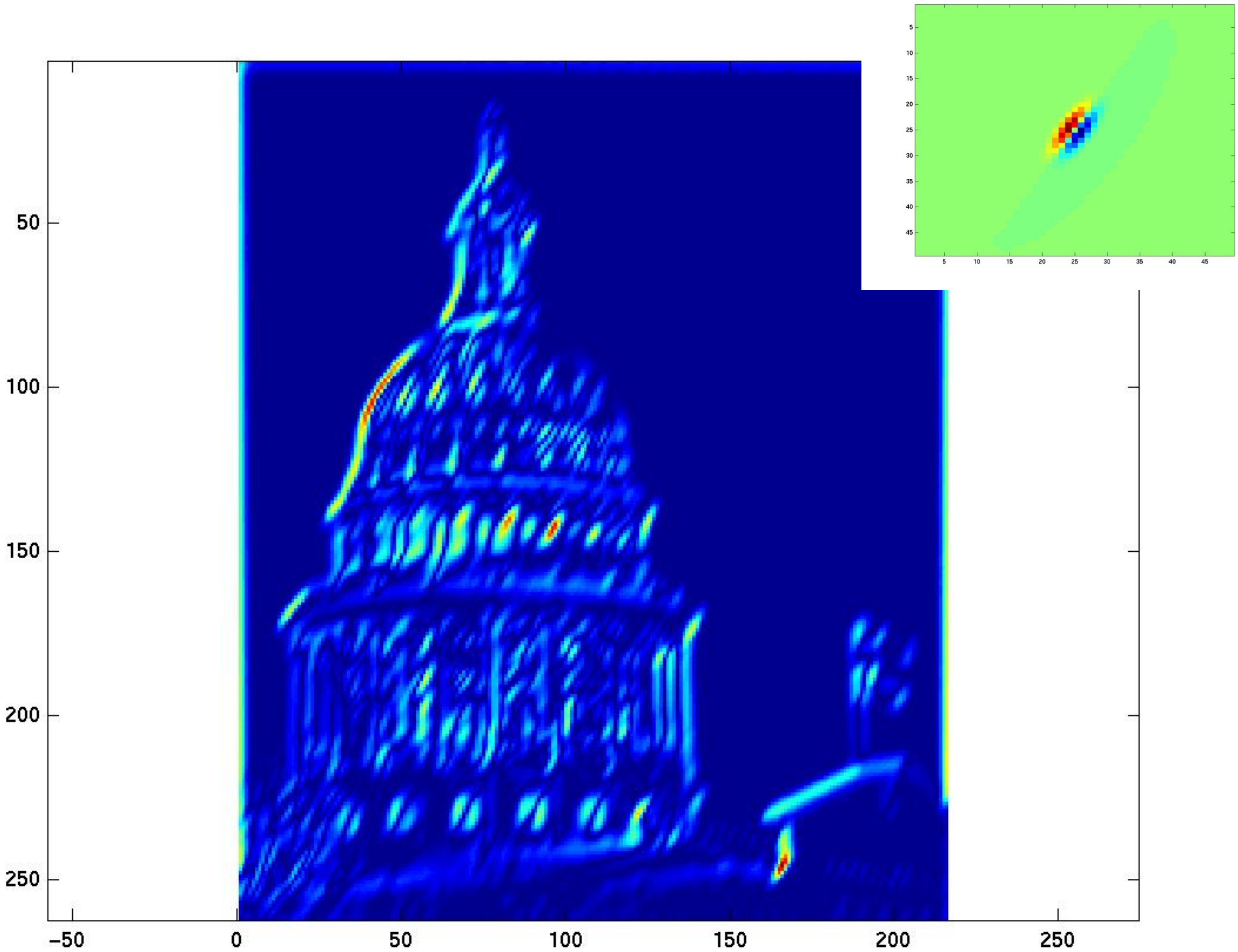

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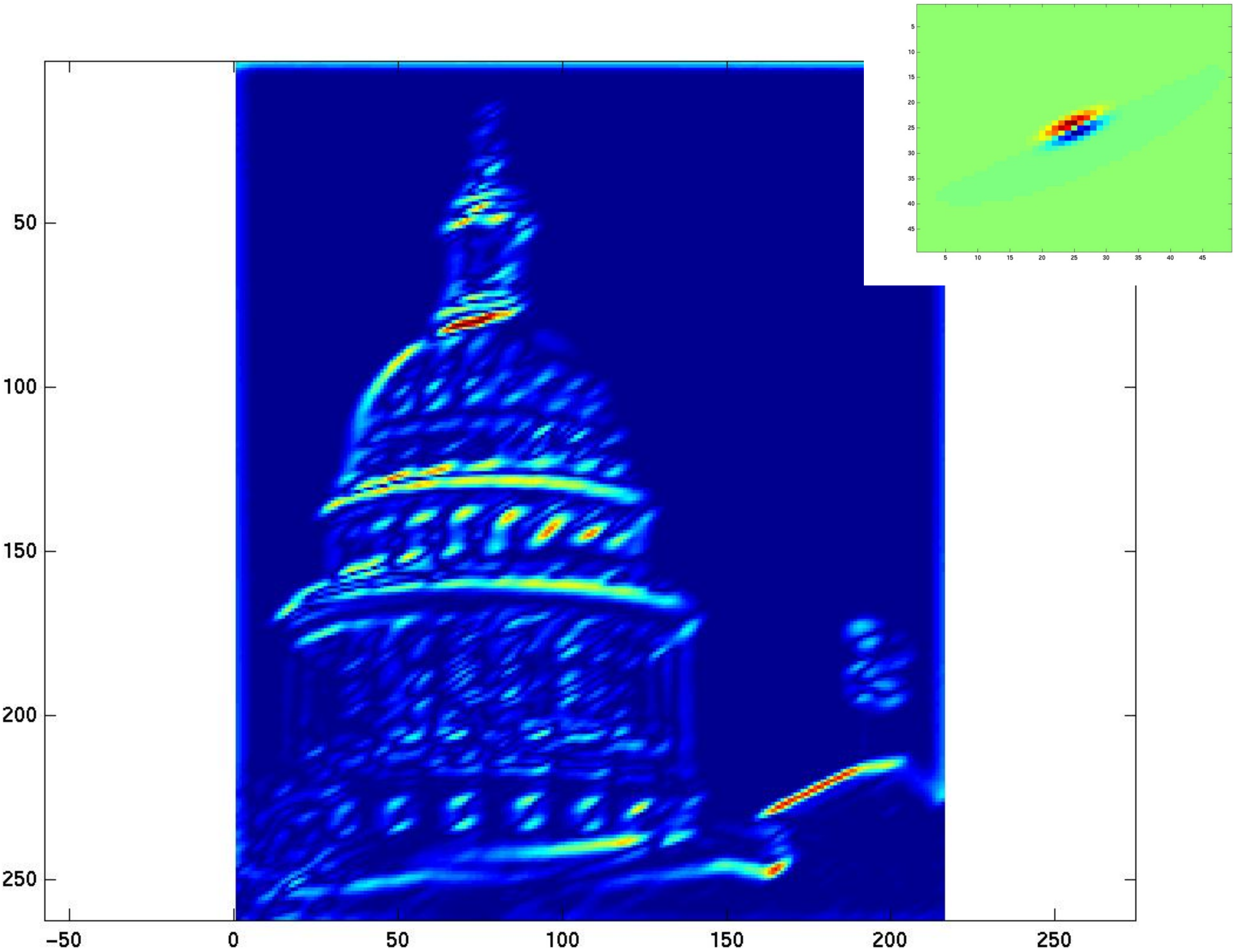

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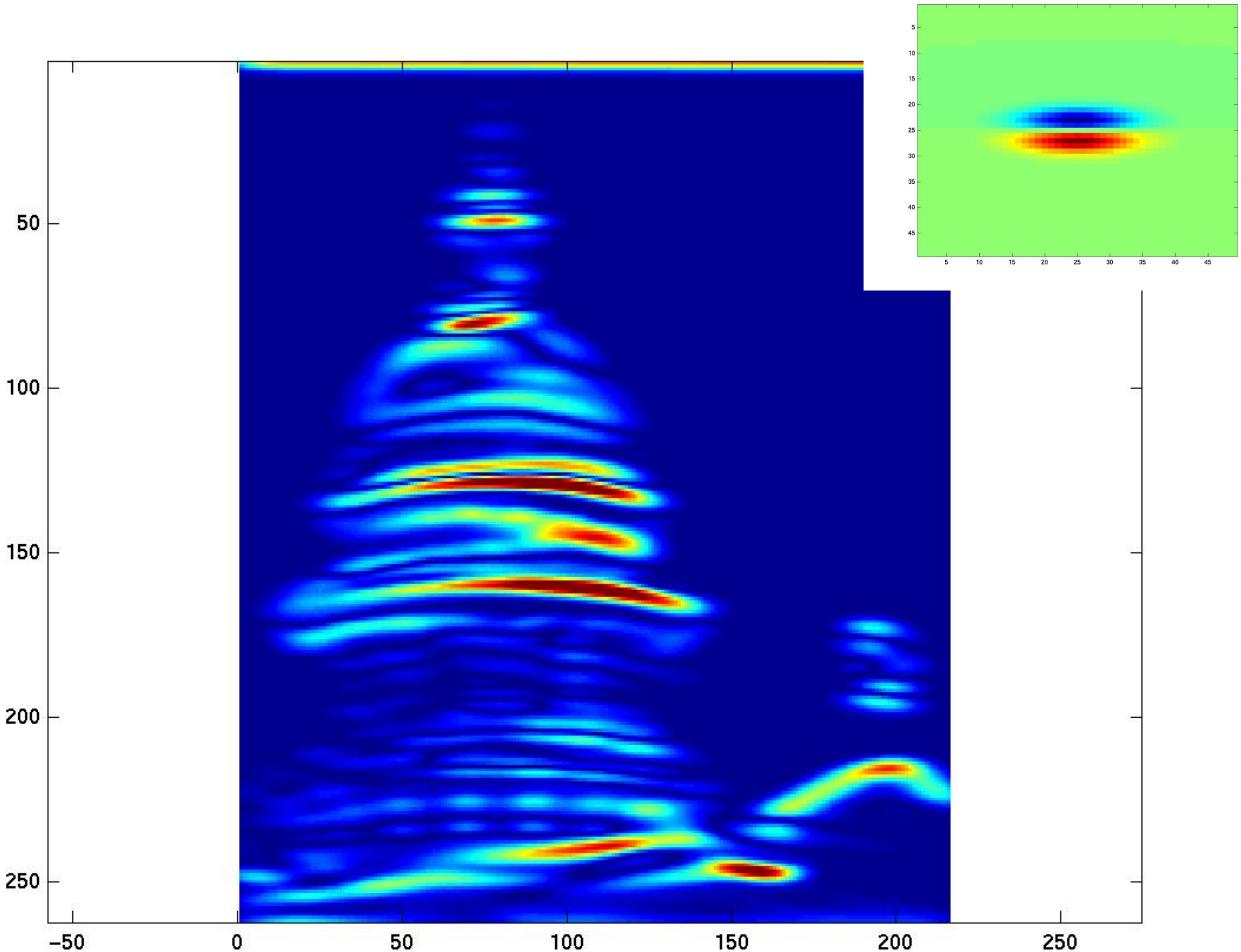

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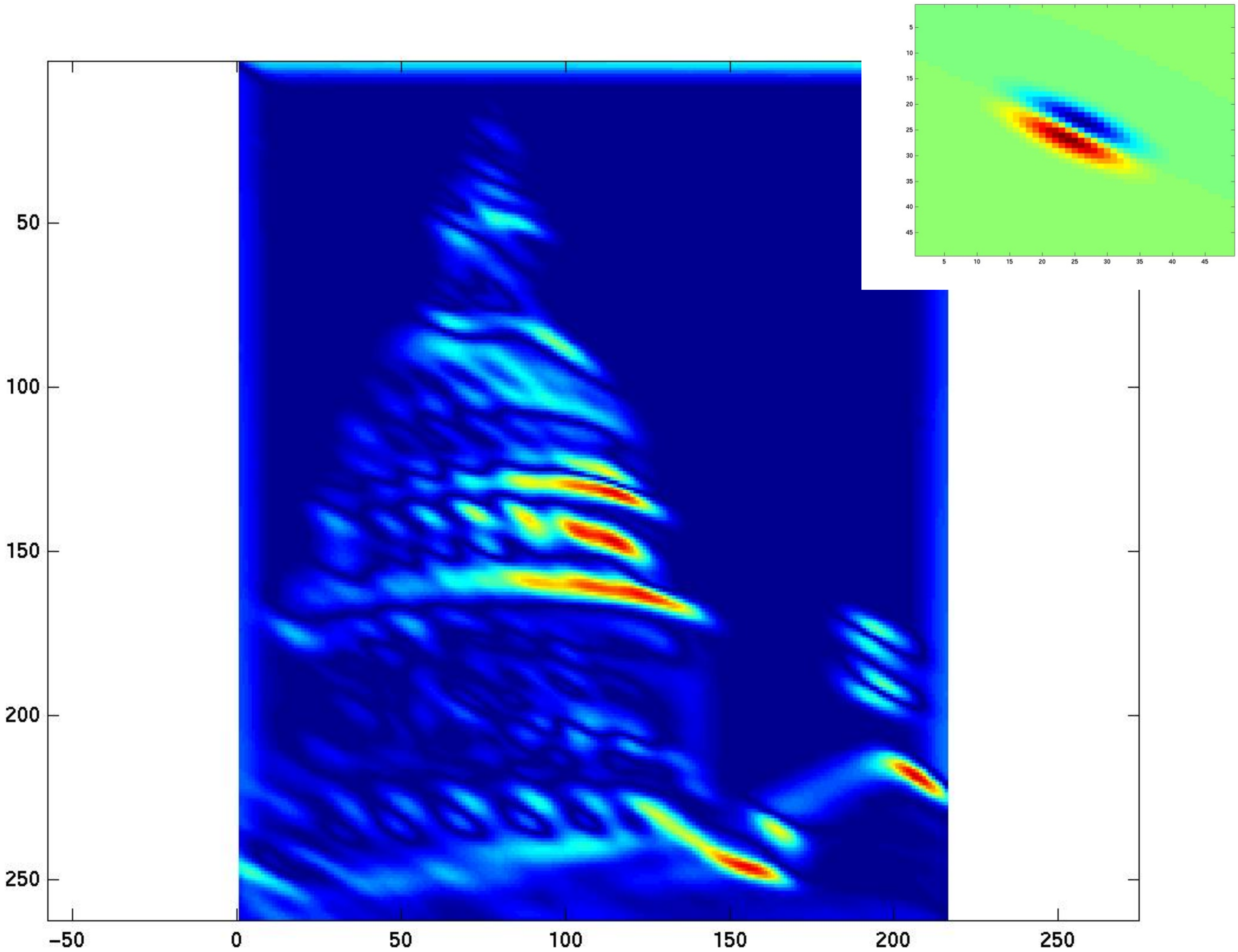

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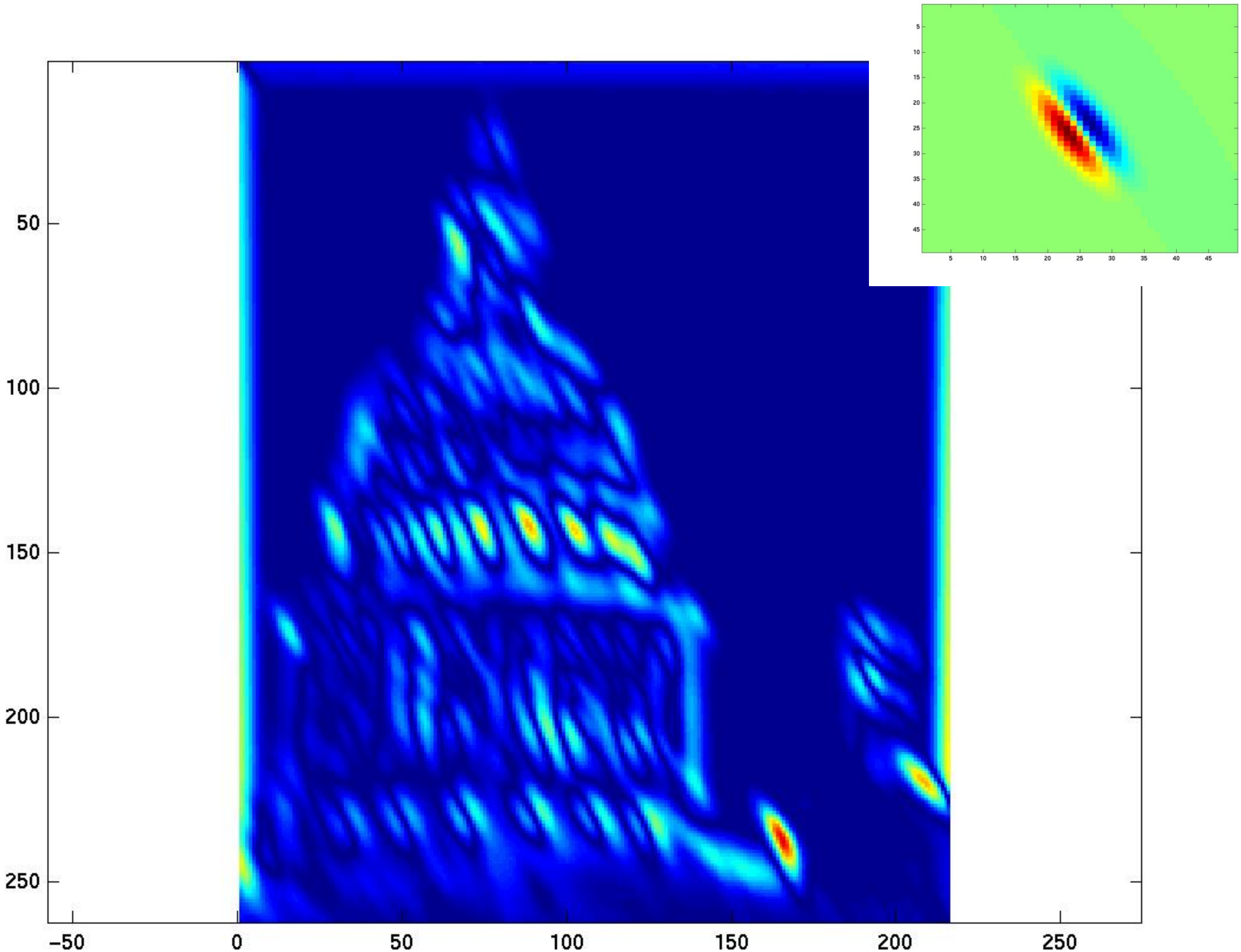

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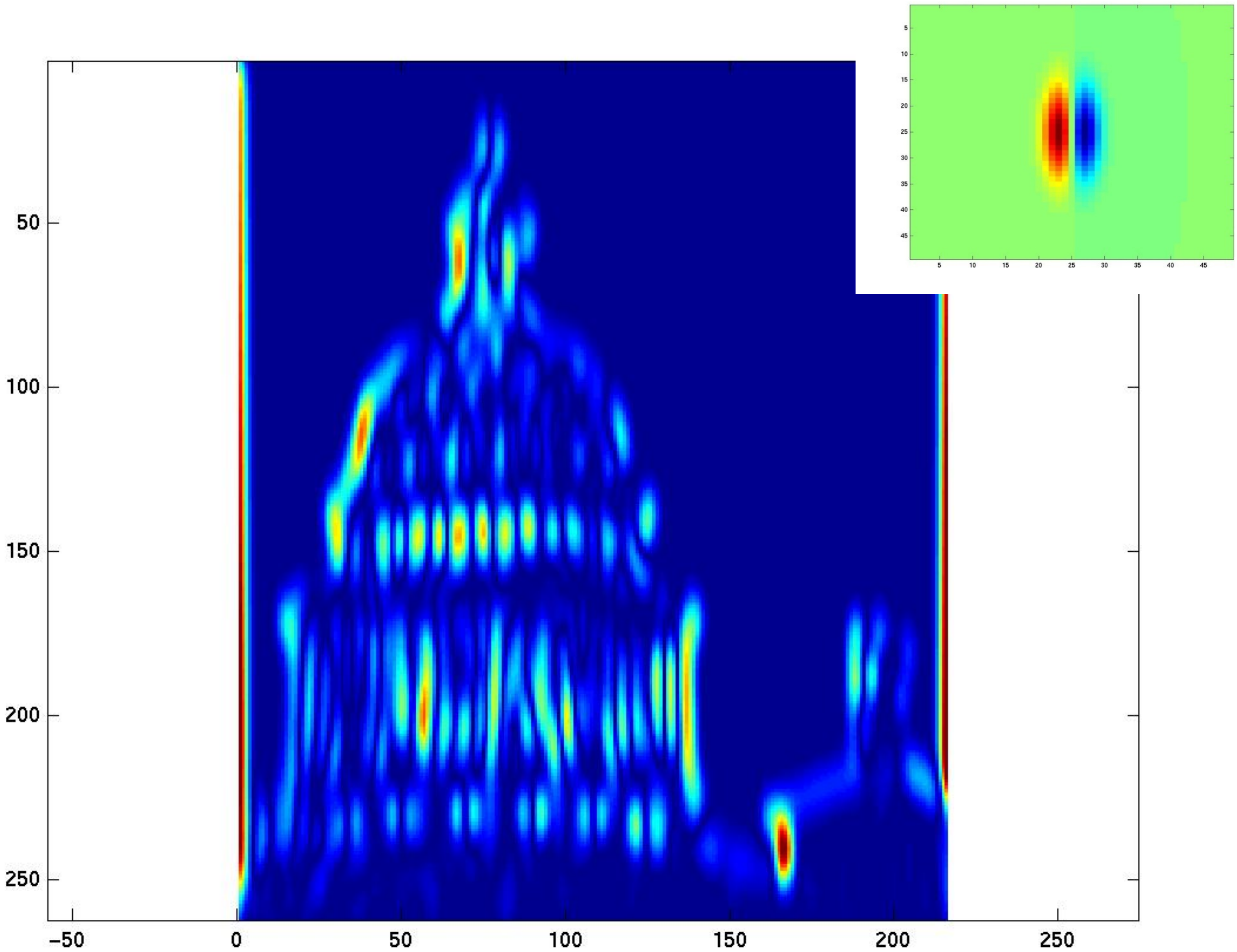

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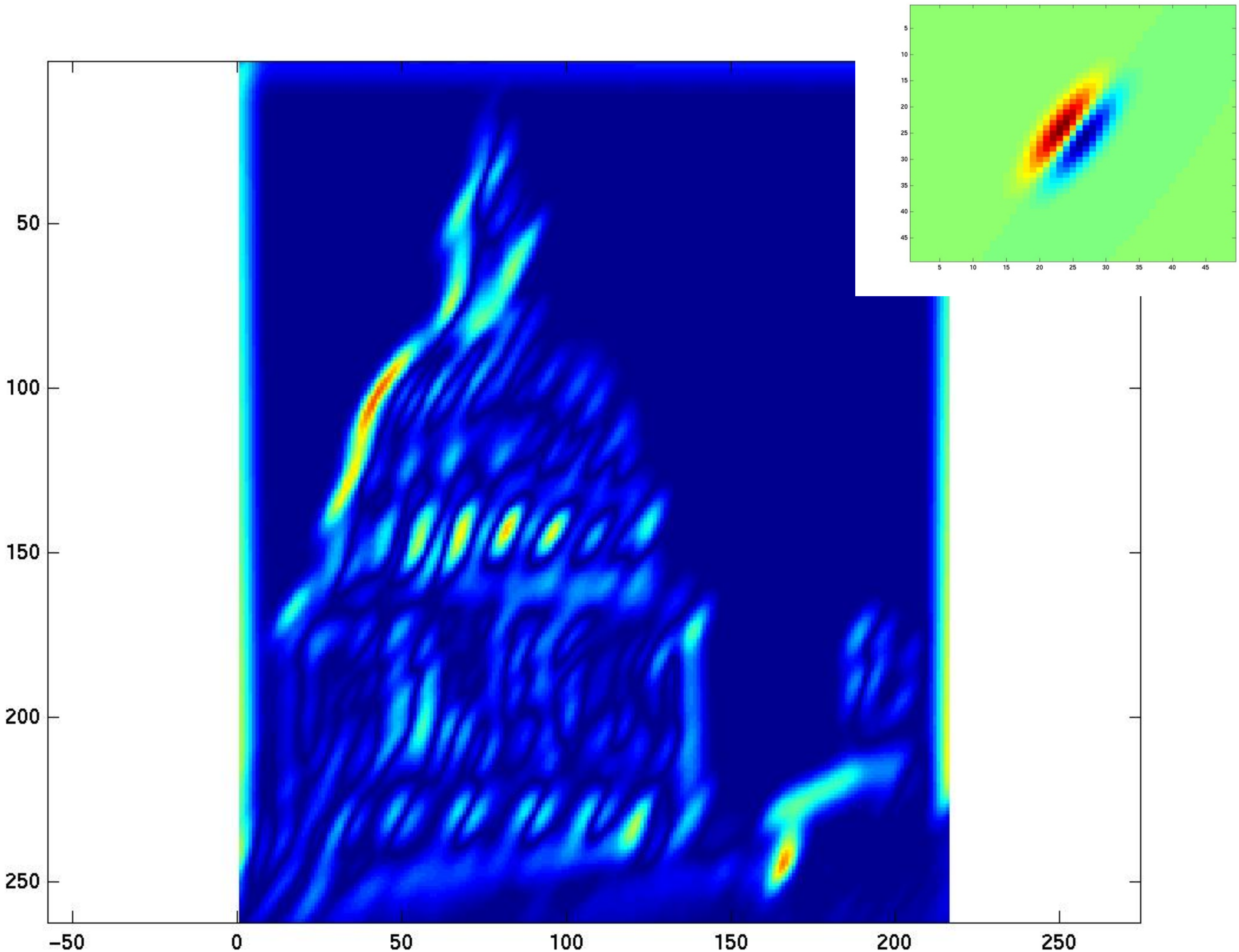
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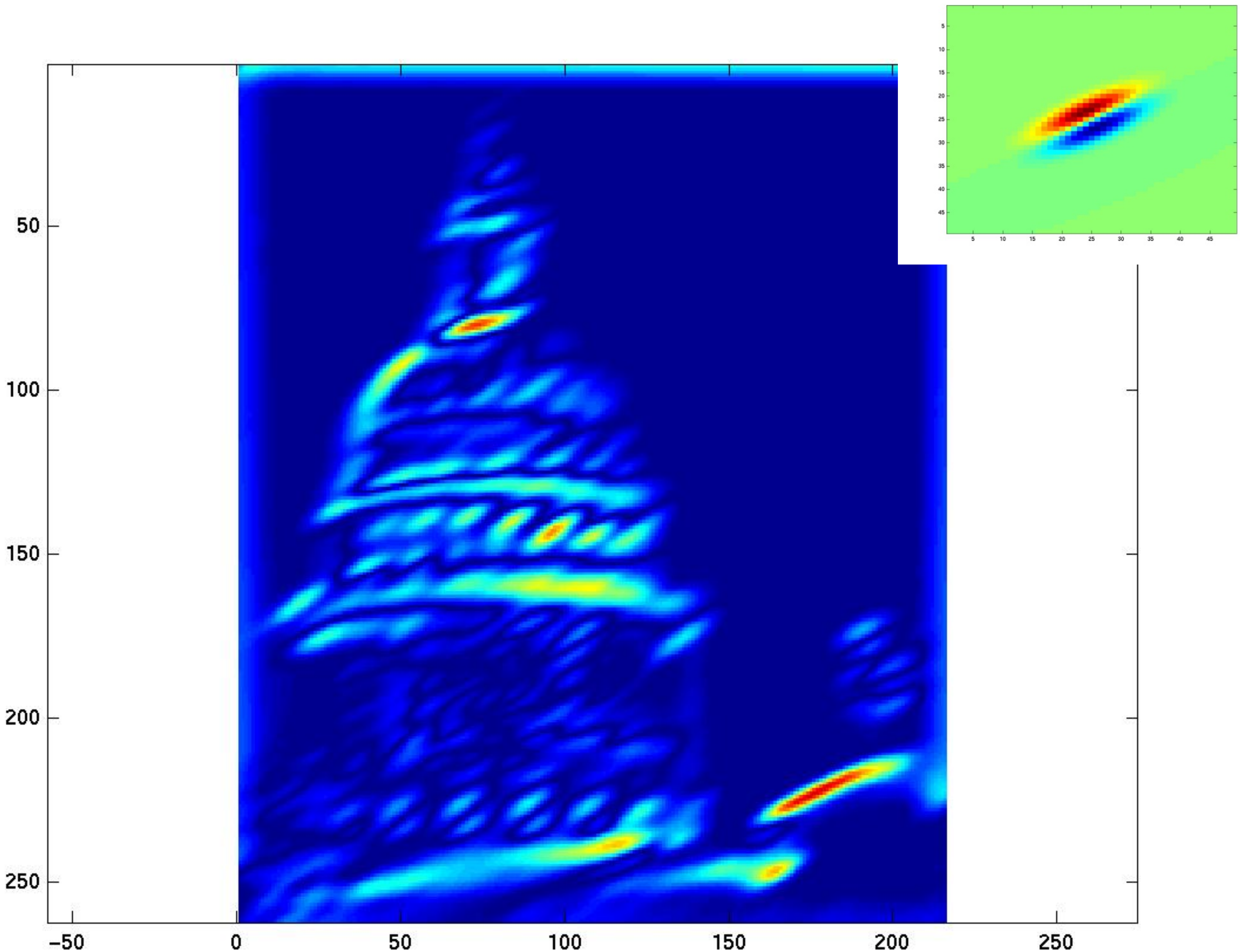

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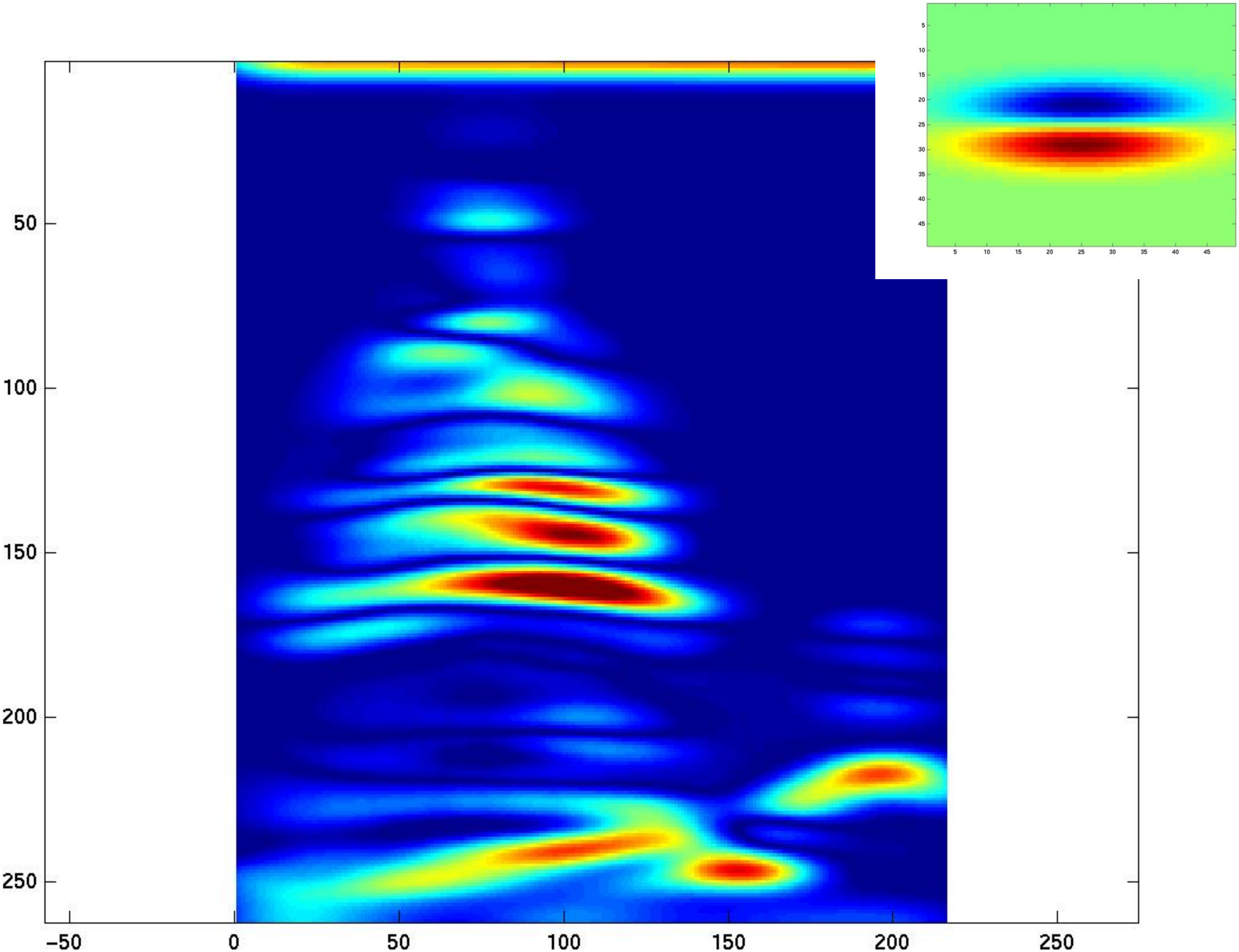

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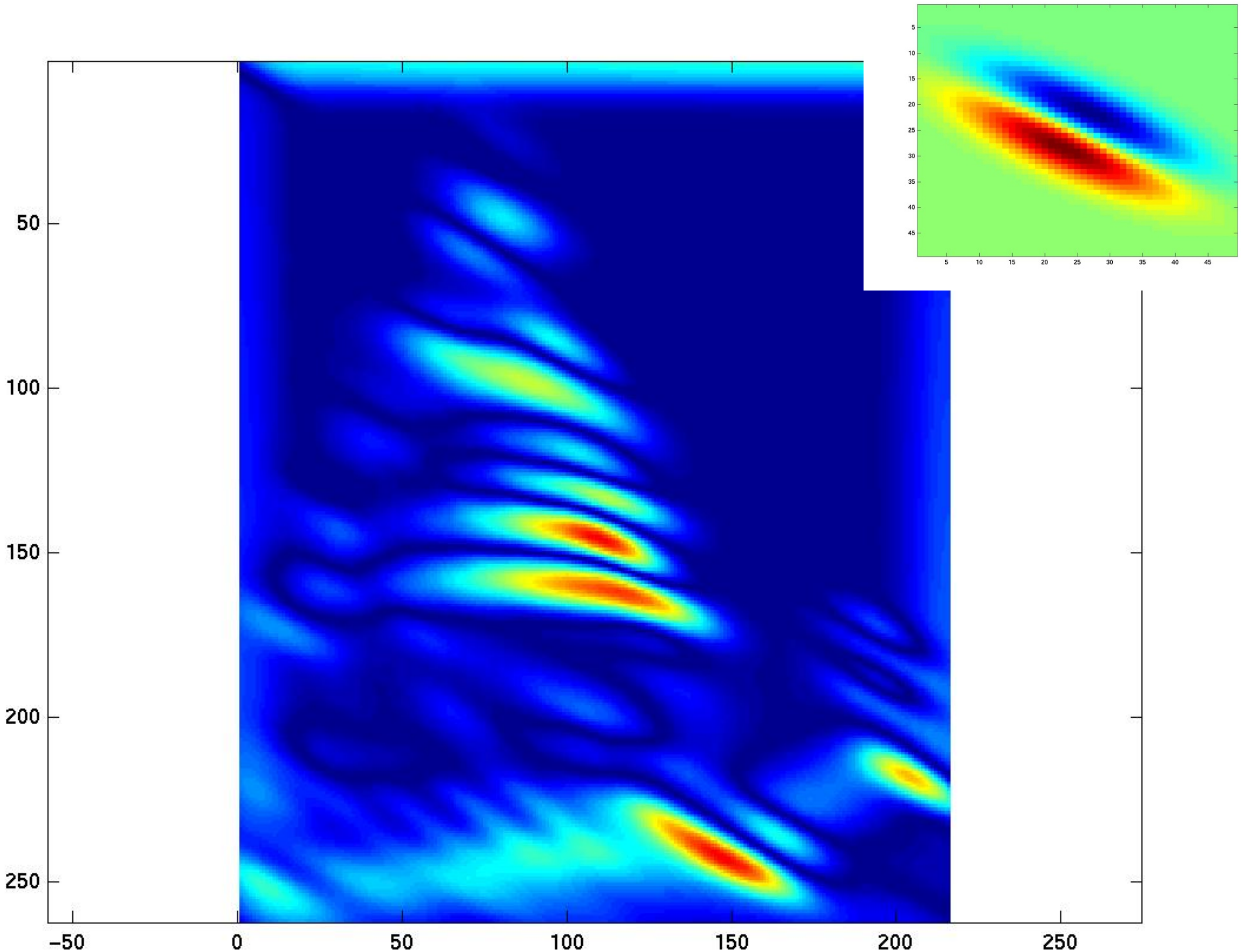

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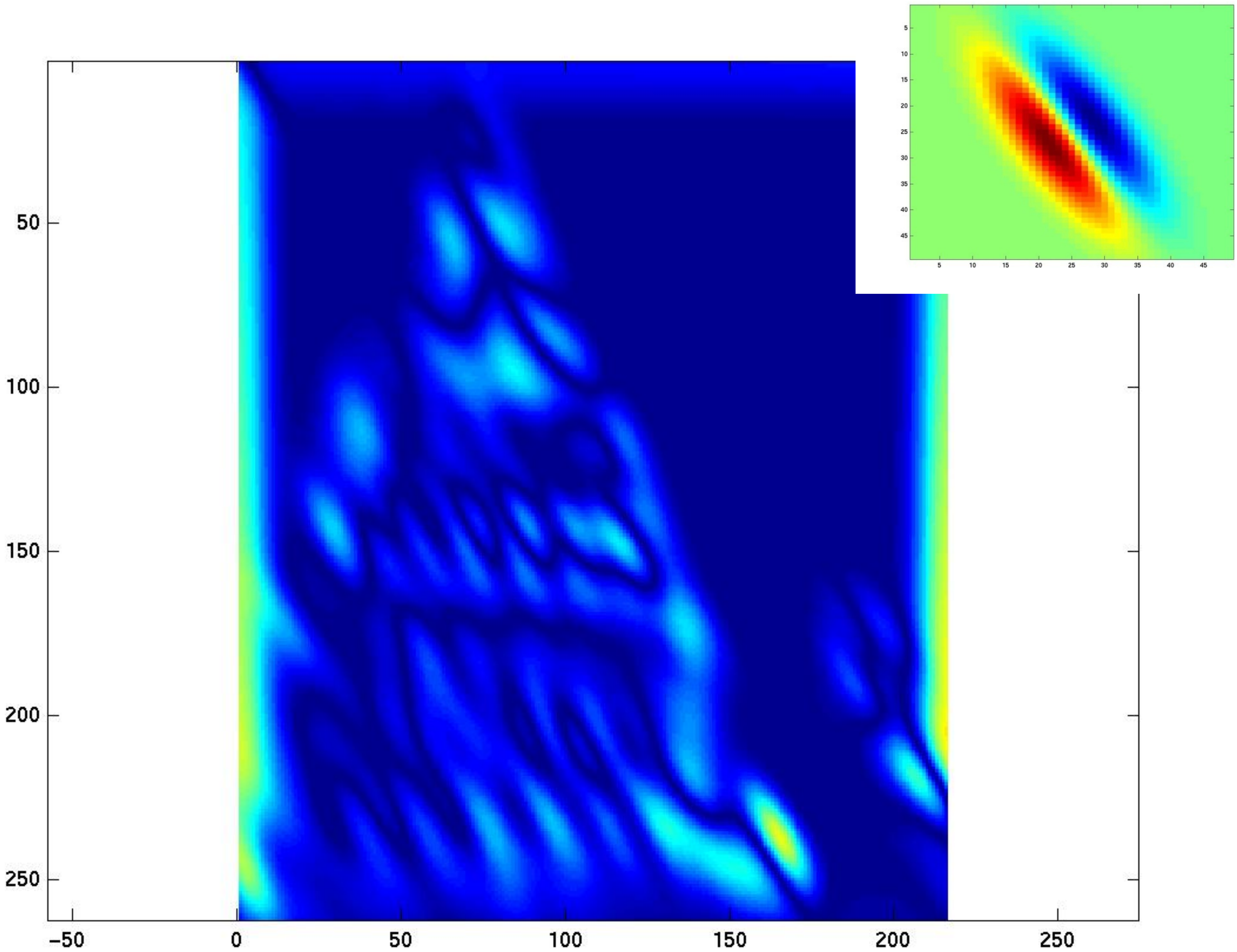

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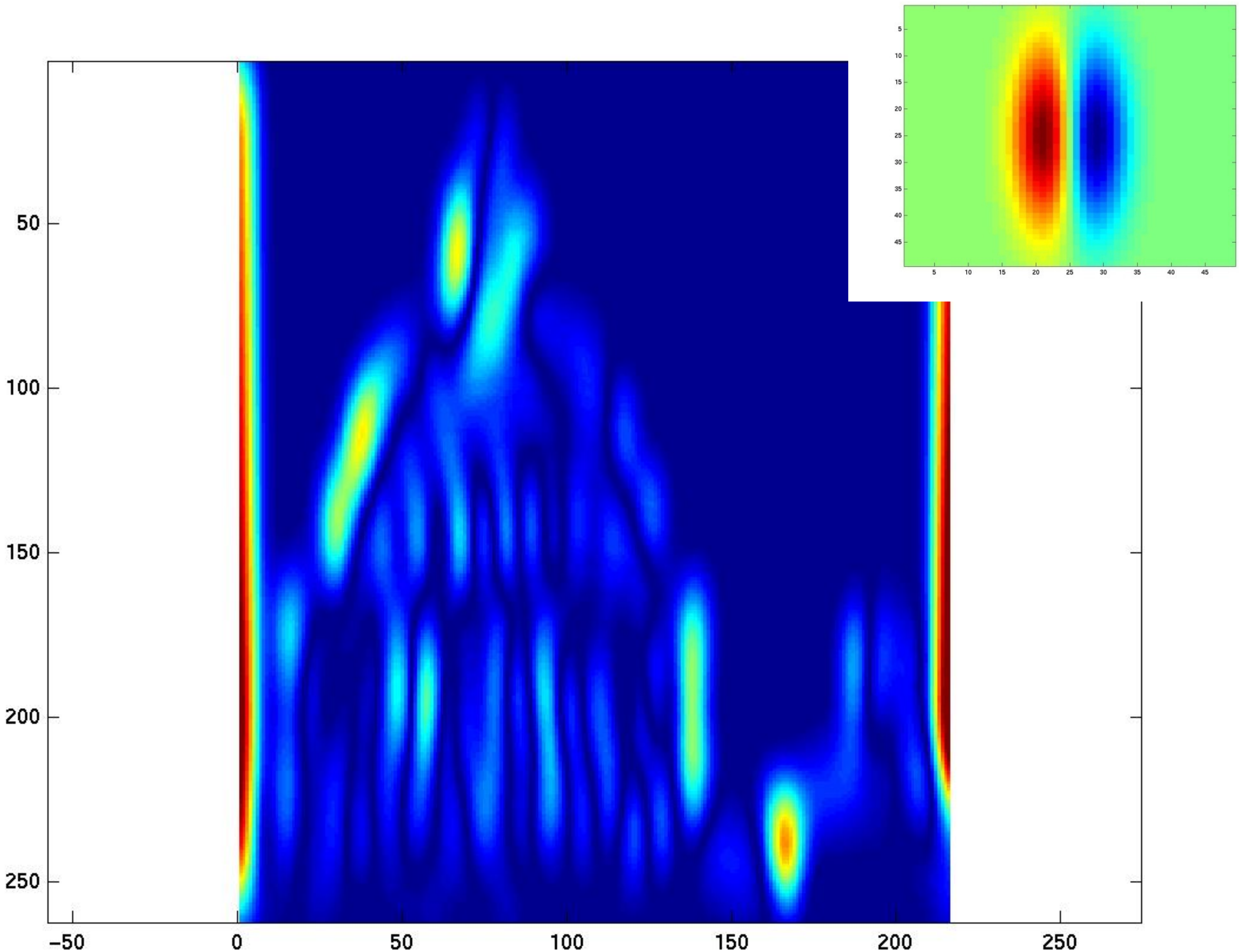

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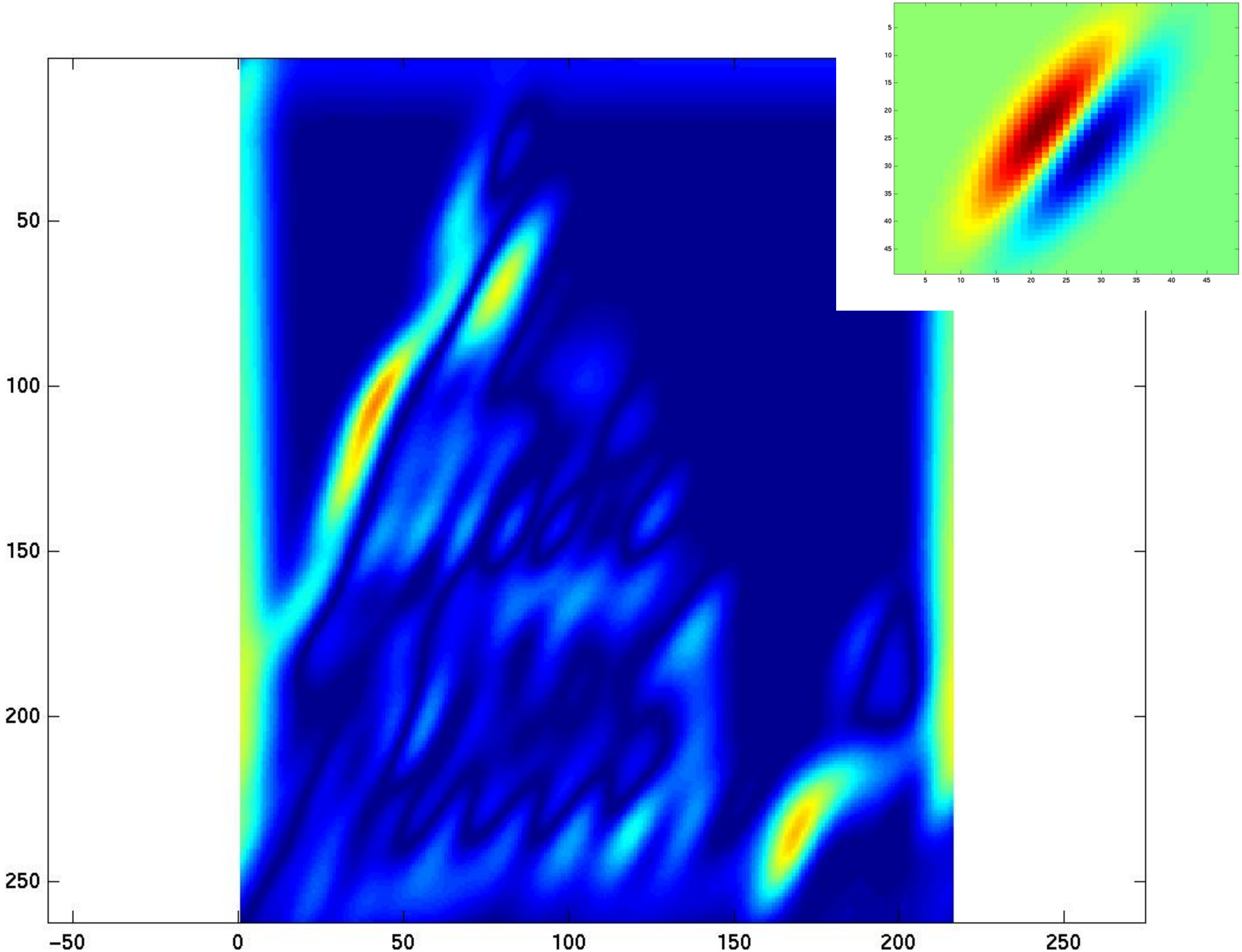

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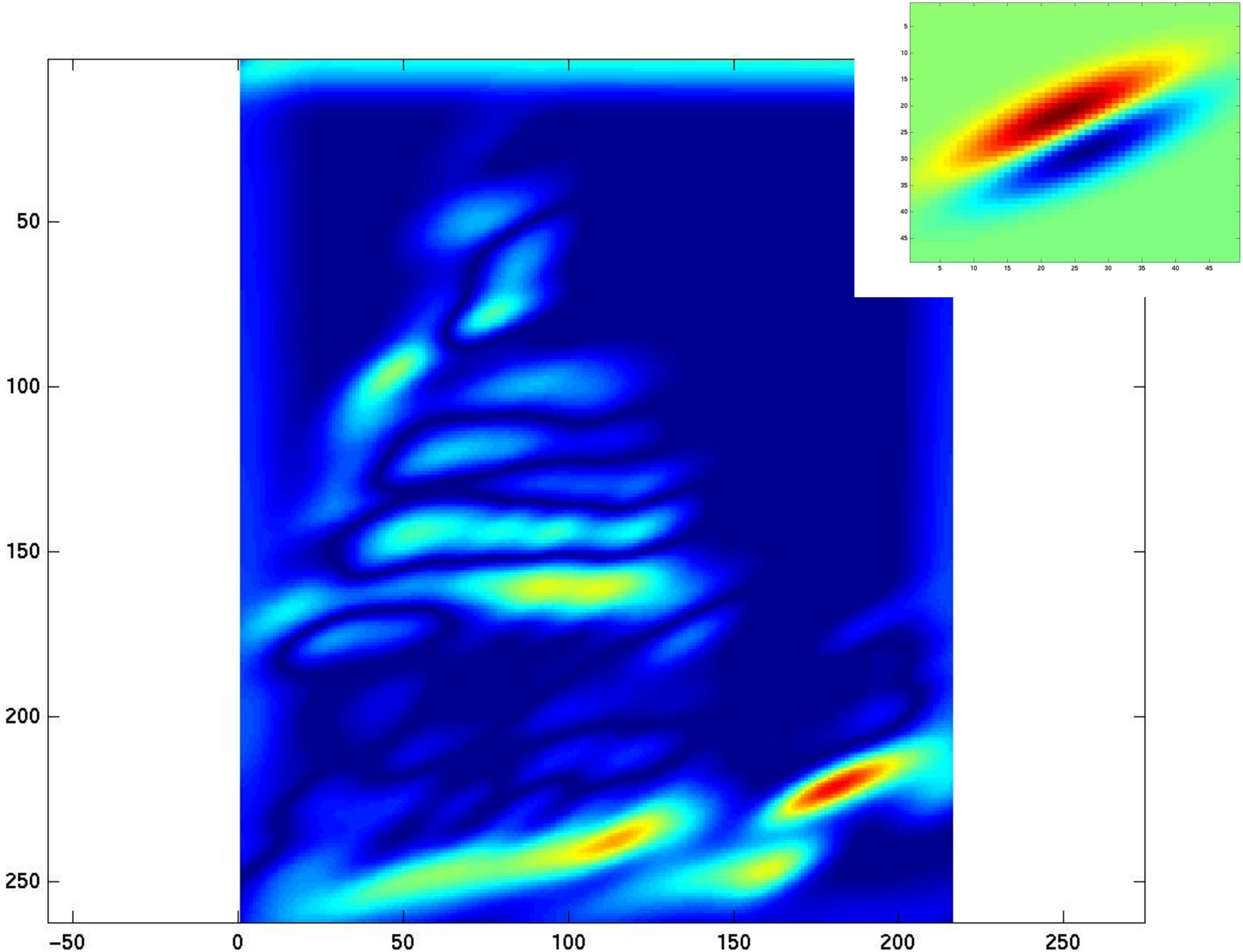

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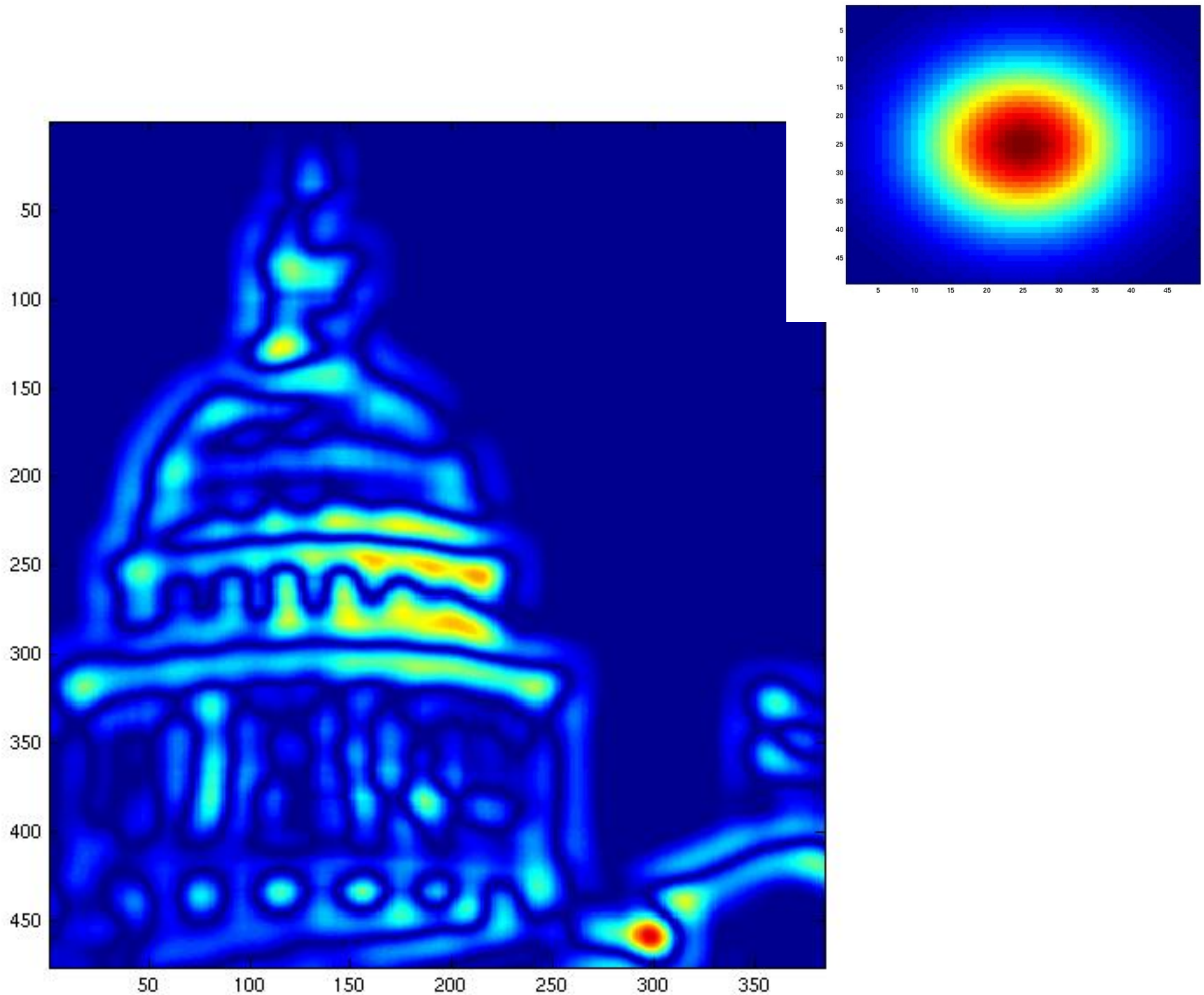
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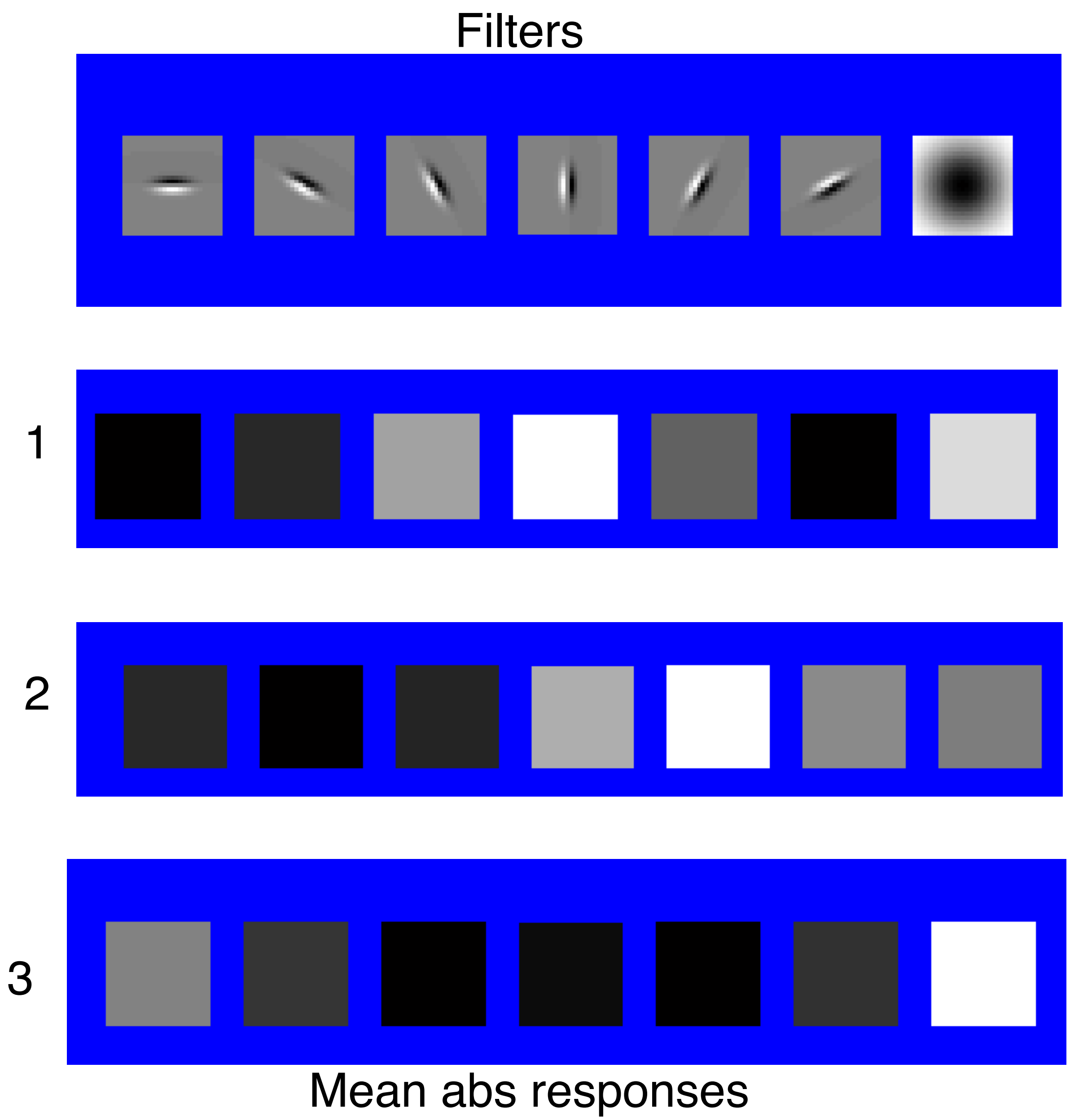
You Try: Can you match the texture to the response?



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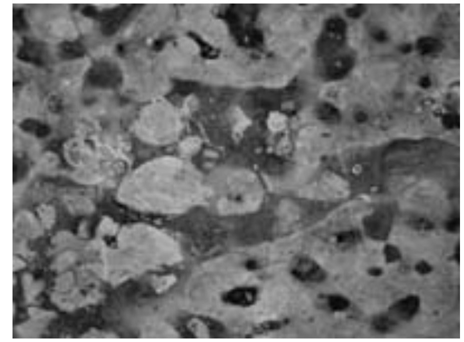
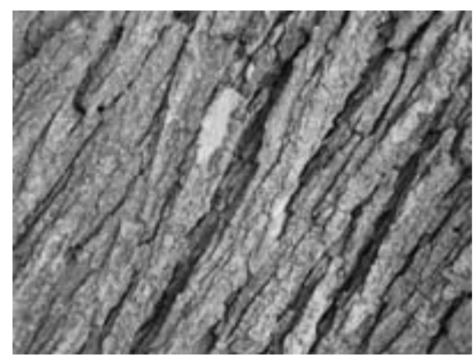


B

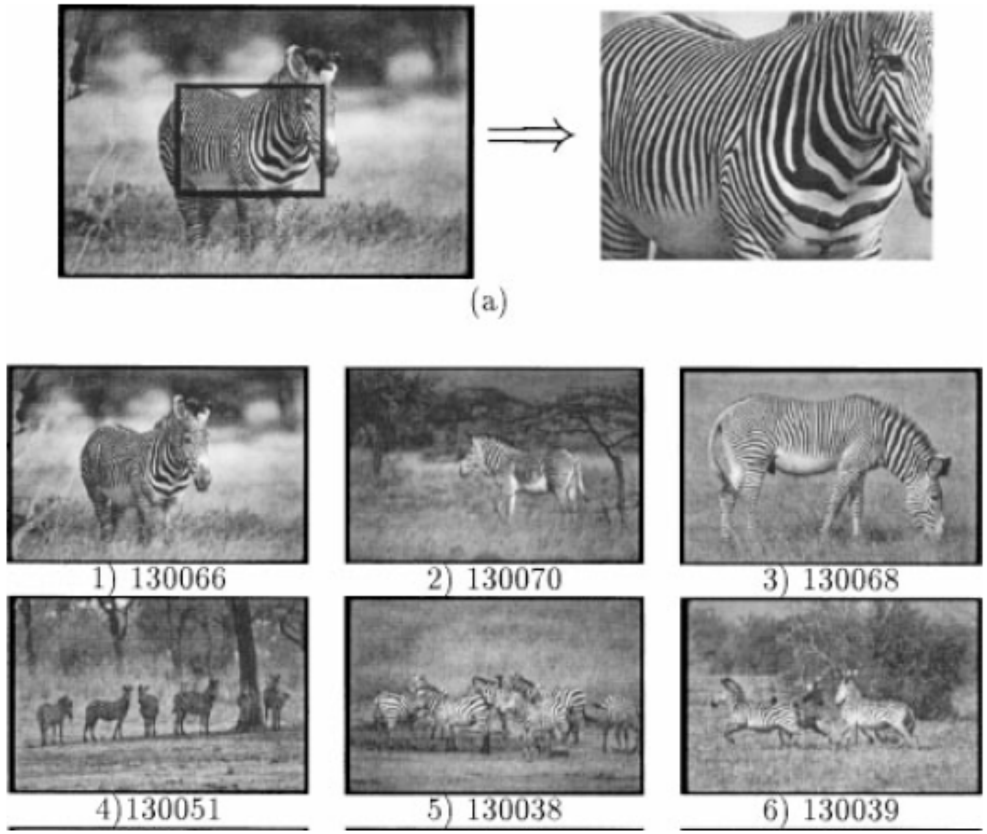
C



Derek Hoiem

Application: Retrieval

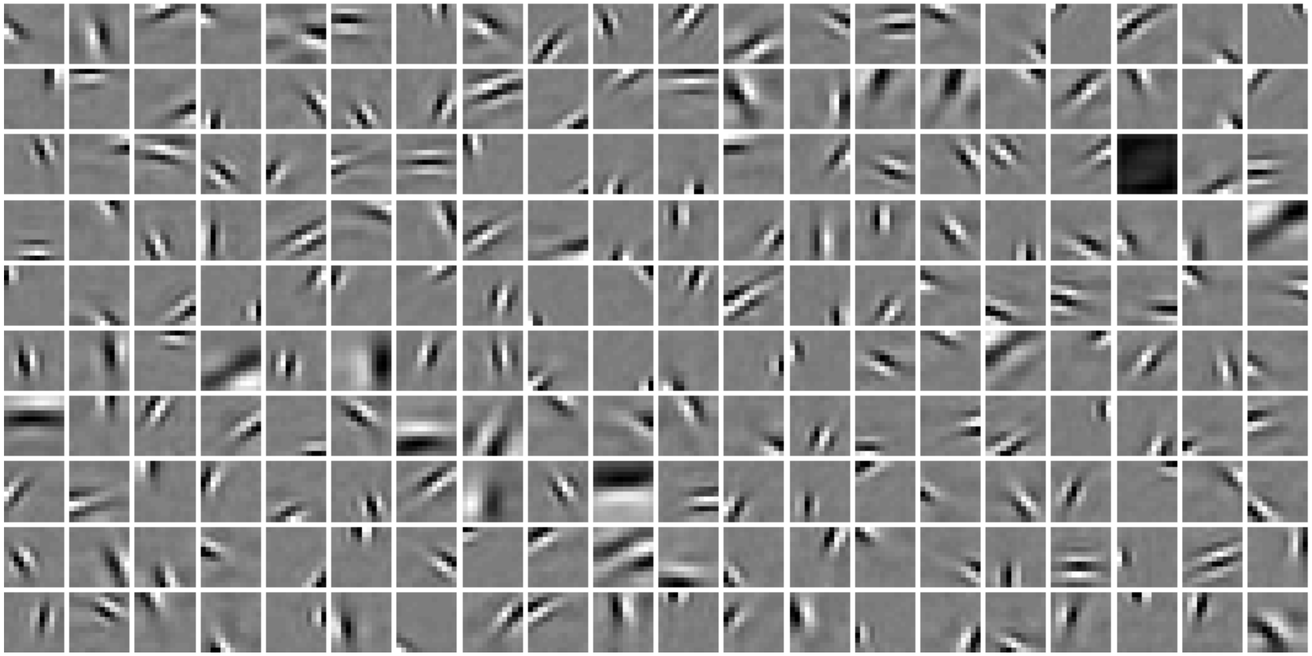
- Retrieve similar images based on texture



Y. Rubner, C. Tomasi, and L. J. Guibas. The earth mover's distance as a metric for image retrieval. *International Journal of Computer Vision*, 40(2): 99-121, November 2000,

Textons

- Elements ("textons") either identical or come from some statistical distribution
- Can analyze in natural images



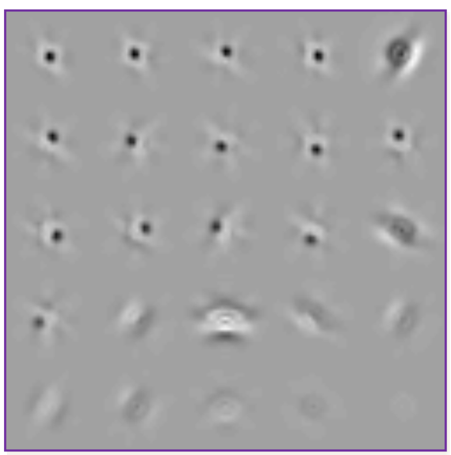
Olhausen & Field

Clustering Textons

- Output of bank of *n* filters can be thought of as vector in *n*-dimensional space
- Can *cluster* these vectors using *k*-means [Malik et al.]
- Result: dictionary of most common textures

Clustering Textons

Image



Clustered Textons

Texton to Pixel Mapping

Malik

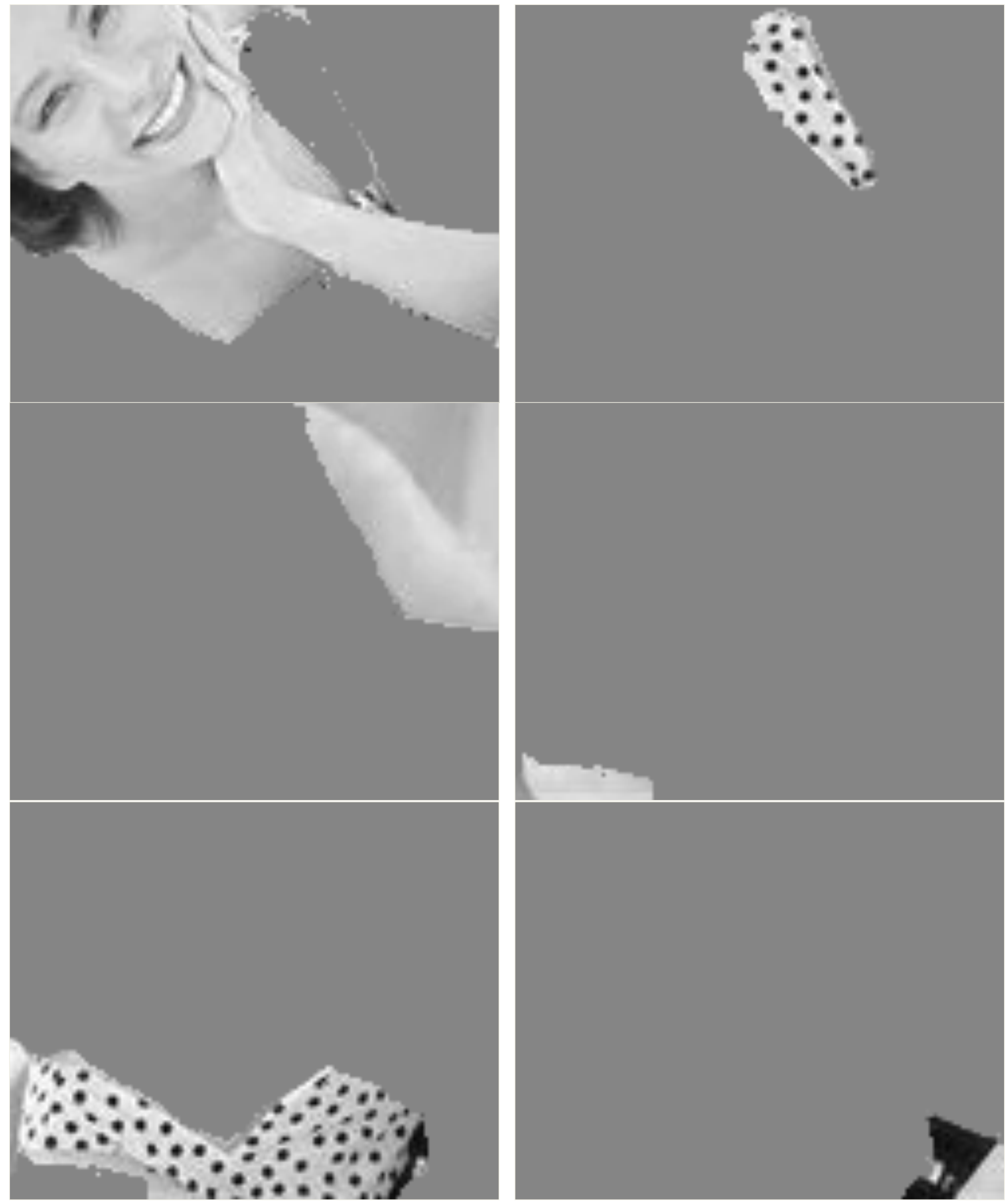
Using Texture in Segmentation

- Compute histogram of how many times each of the *k* clusters occurs in a neighborhood
- Define similarity of histograms h_i and h_j using χ^2

$$\chi^2 = \frac{1}{2} \sum_k \frac{(h_i(k) - h_j(k))^2}{h_i(k) + h_j(k)}$$

- Different histograms → separate regions

Application: Segmentation



Malik

Texture synthesis

Markov Random Fields

- Different way of thinking about textures
- Premise: probability distribution of a pixel depends on values of neighbors
- Probability the same throughout image
  - Extension of Markov chains

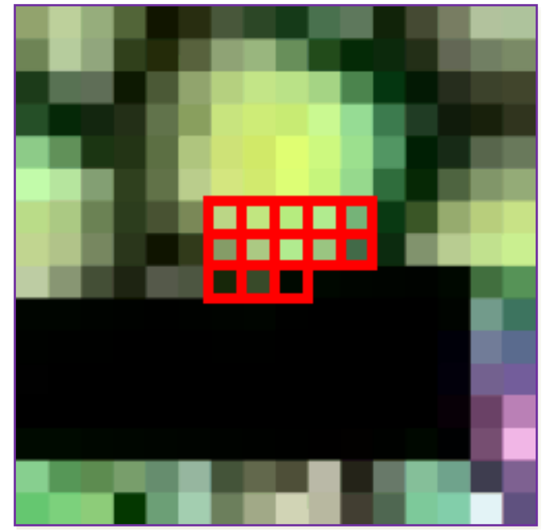
Motivation from Language

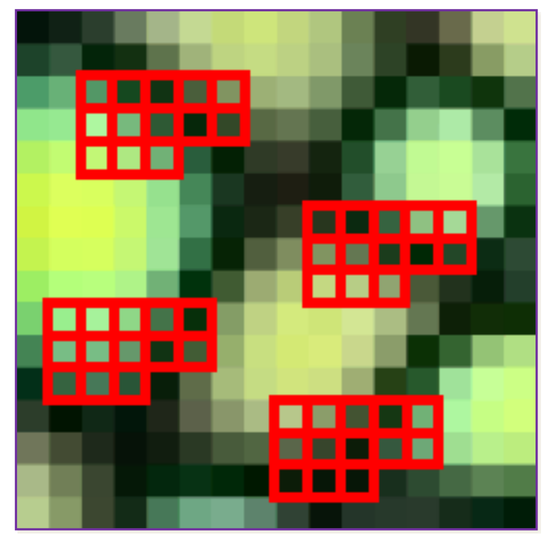
- Shannon (1948) proposed a way to synthesize new text using N-grams
  - Use a large text to compute probability distributions of each letter given N–1 previous letters
  - Starting from a seed repeatedly sample the conditional probabilities to generate new letters
  - Can do this with image patches!

Efros

Texture Synthesis Based on MRF

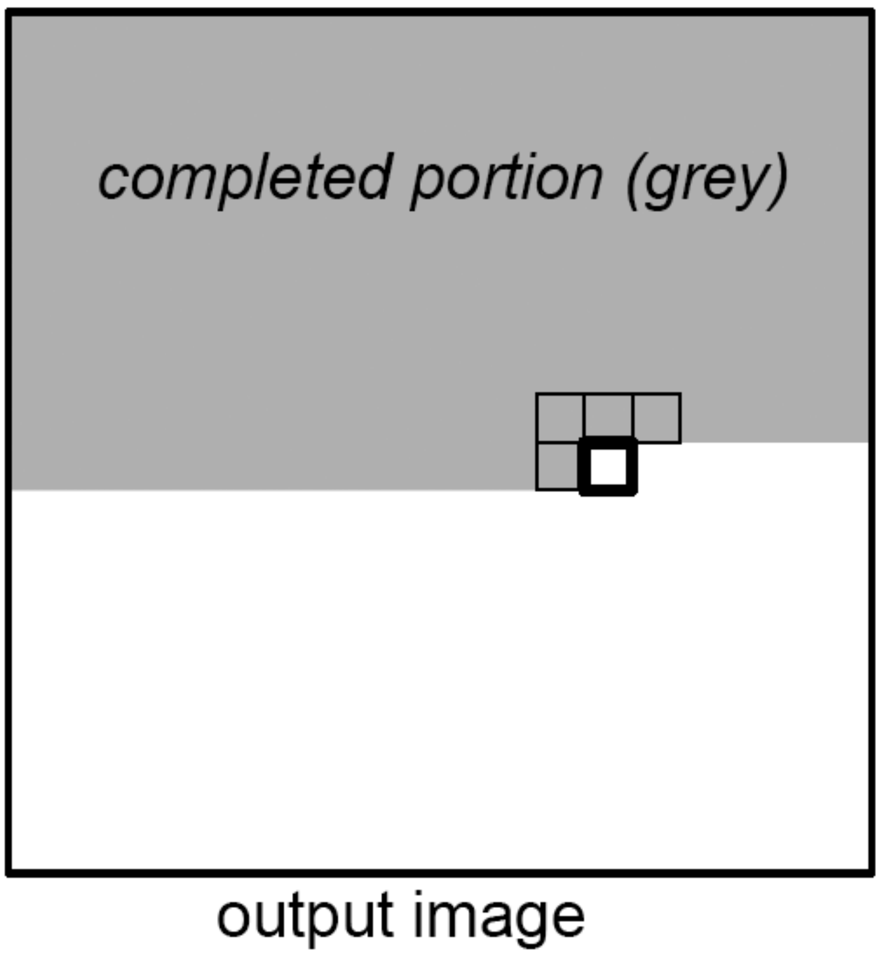
- For each pixel in destination:
  - Take already-synthesized neighbors
  - Find closest match in original texture
  - Copy pixel to destination
- Efros & Leung 1999
  - Speedup by Wei & Levoy 2000
  - Extension to copying whole blocks by Efros & Freeman 2001





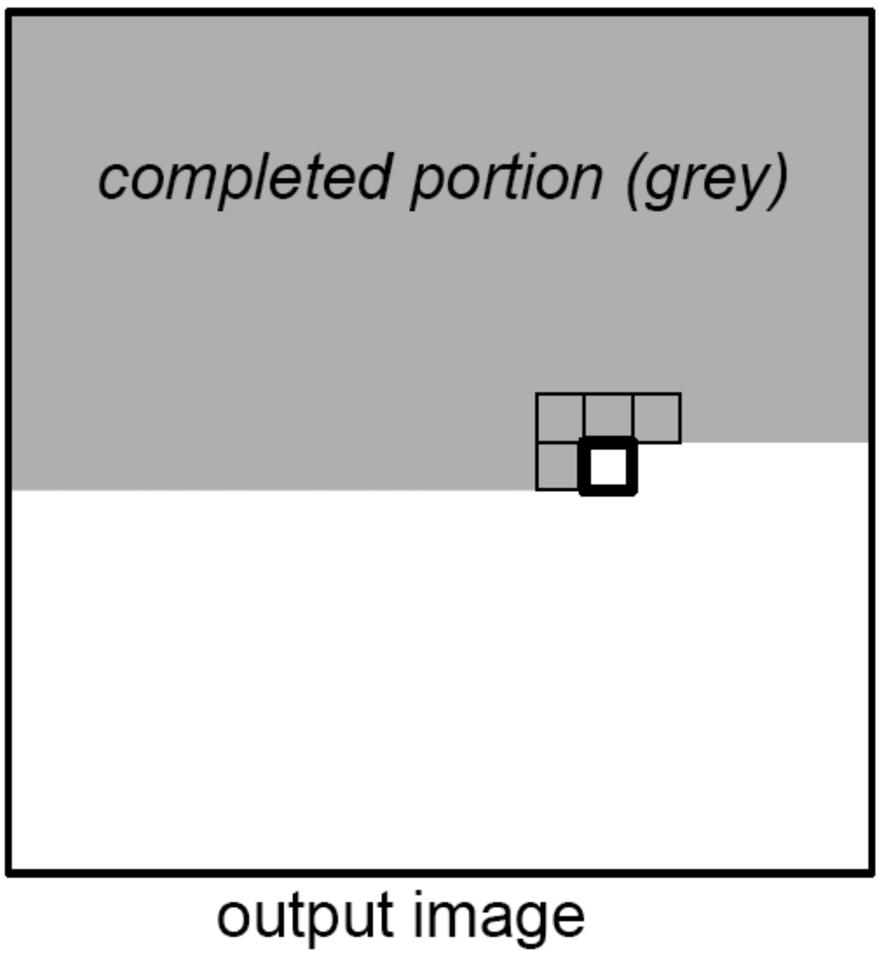
Wei & Levoy

Efros & Leung Algorithm

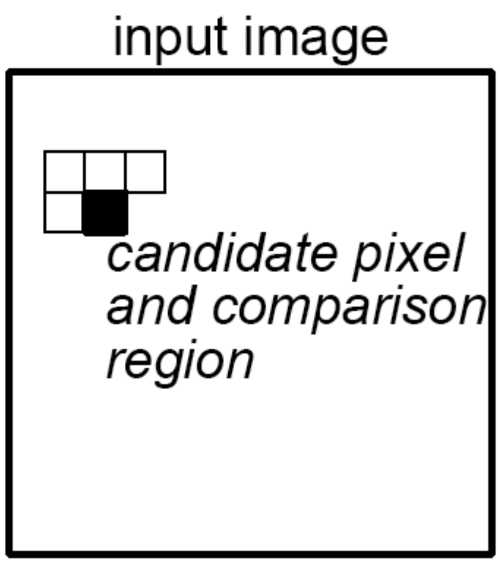


- Compute output pixels in scanline order (top-to-bottom, left-to-right)

Efros & Leung Algorithm



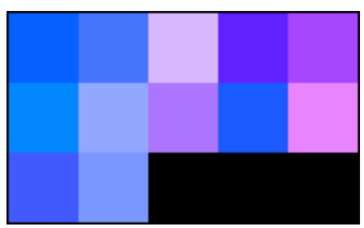
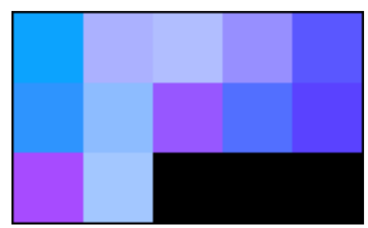
- Find candidate pixels based on similarities of pixel features in neighborhoods



Efros

Efros & Leung Algorithm

- Similarities of pixel neighborhoods can be computed with squared differences (SSD) of pixel colors and/or filter bank responses

$||($  $-$  $)||^2$

Efros

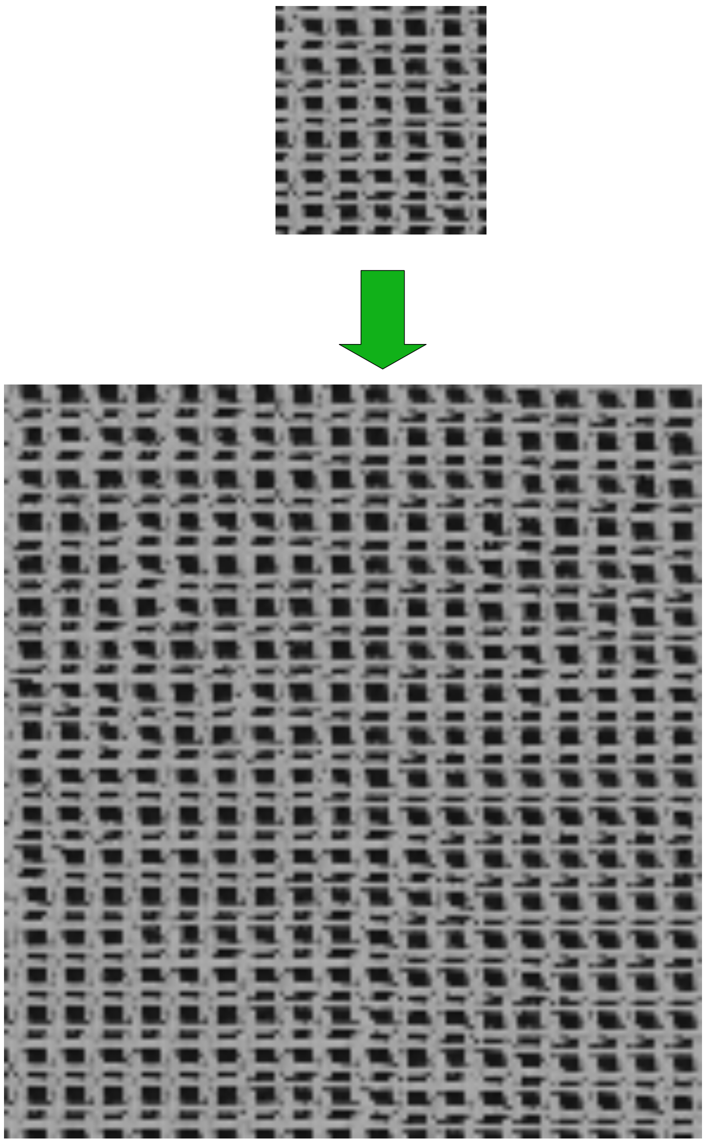
Efros & Leung Algorithm

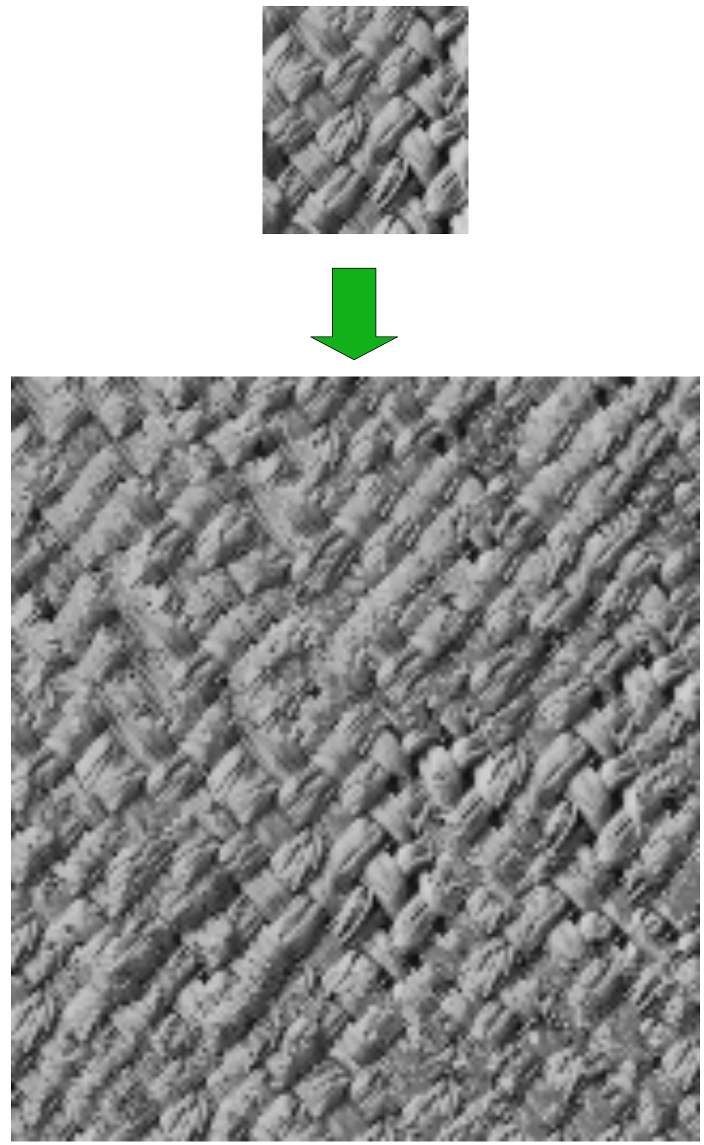
- For each pixel p:
  - Find the best matching K windows from the input image
  - Pick one matching window at random
  - Assign p to be the center pixel of that window

input image

Efros

Synthesis Results



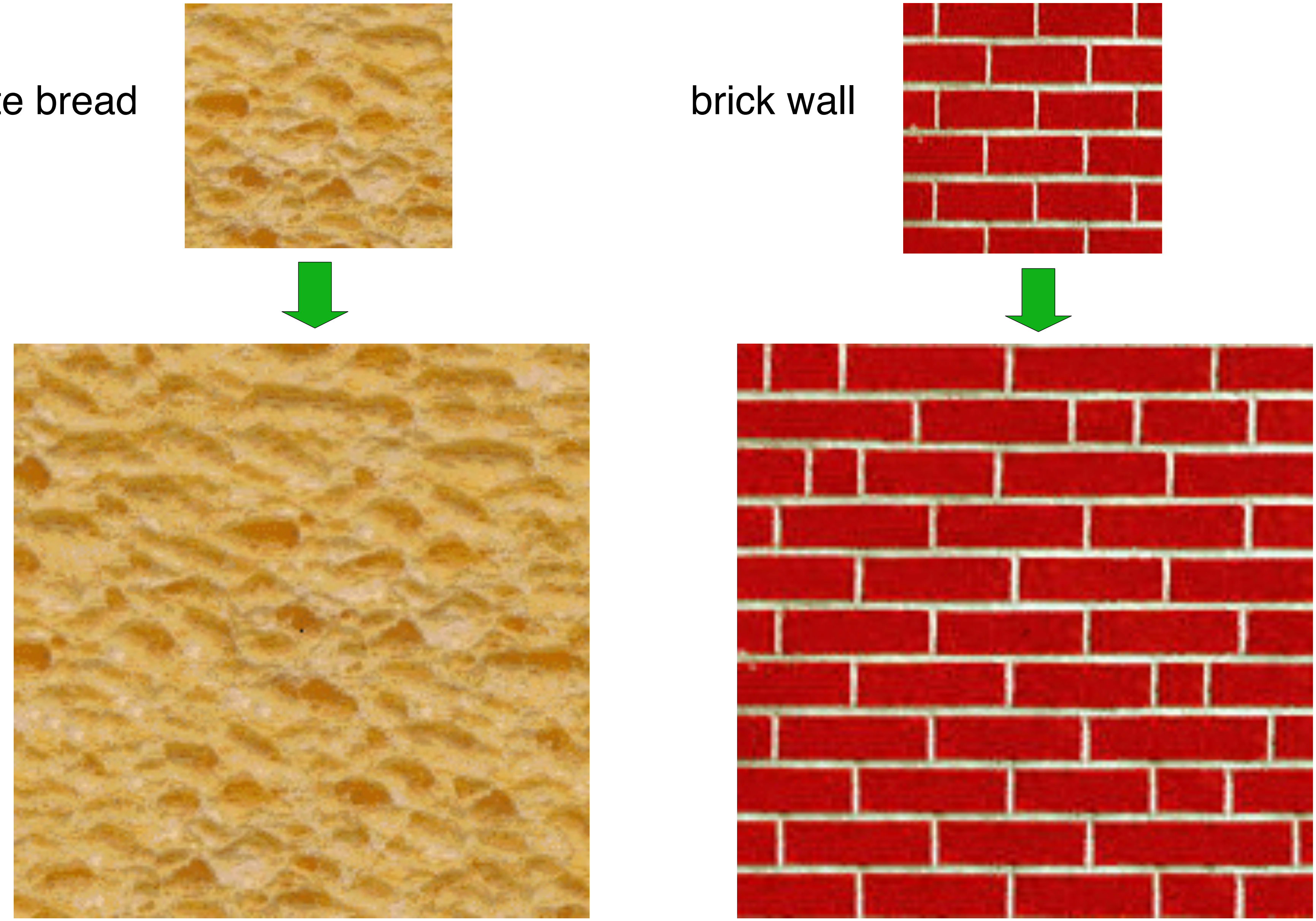


Efros

Synthesis Results

white bread

brick wall

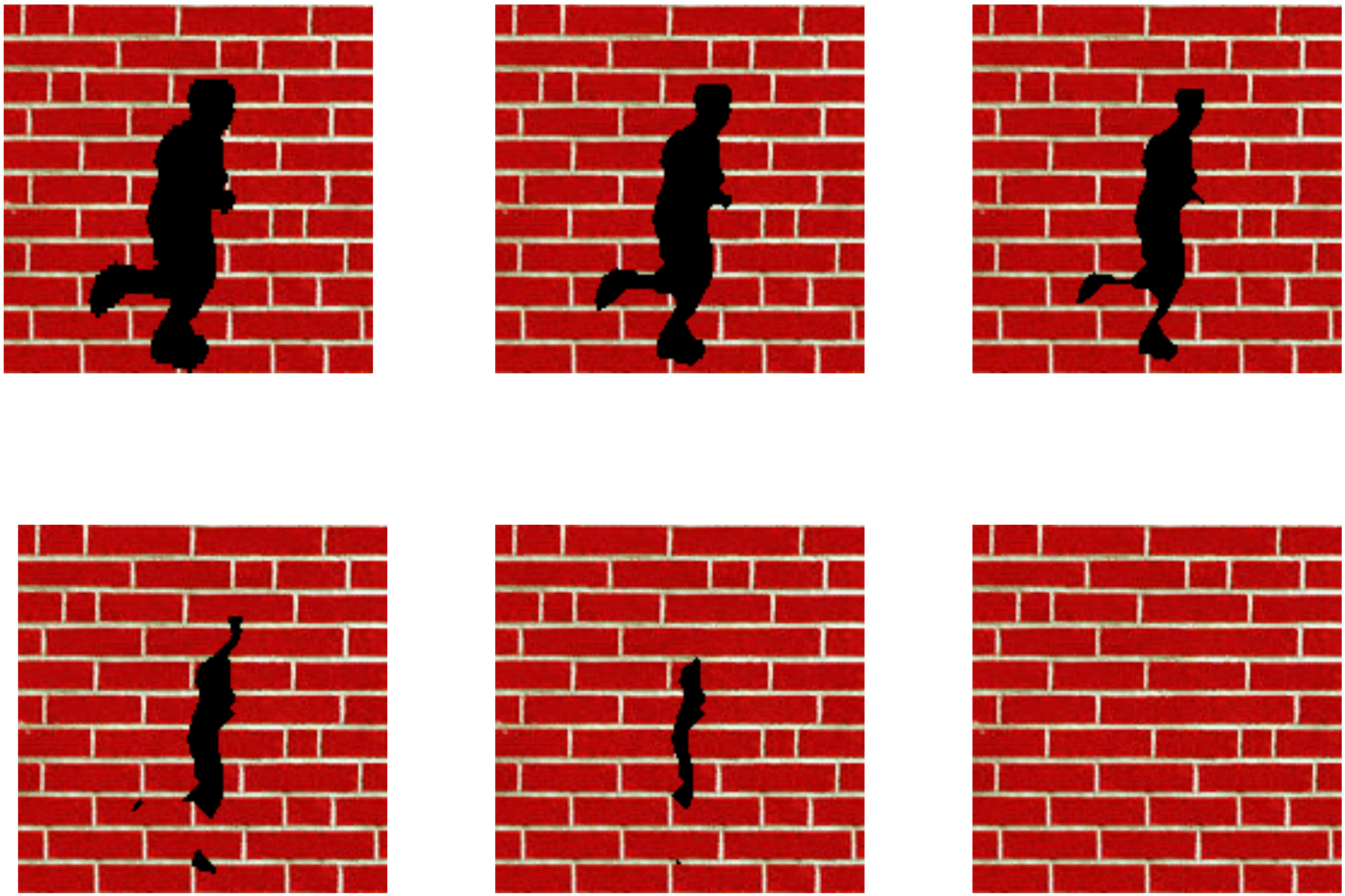


Efros

Hole Filling

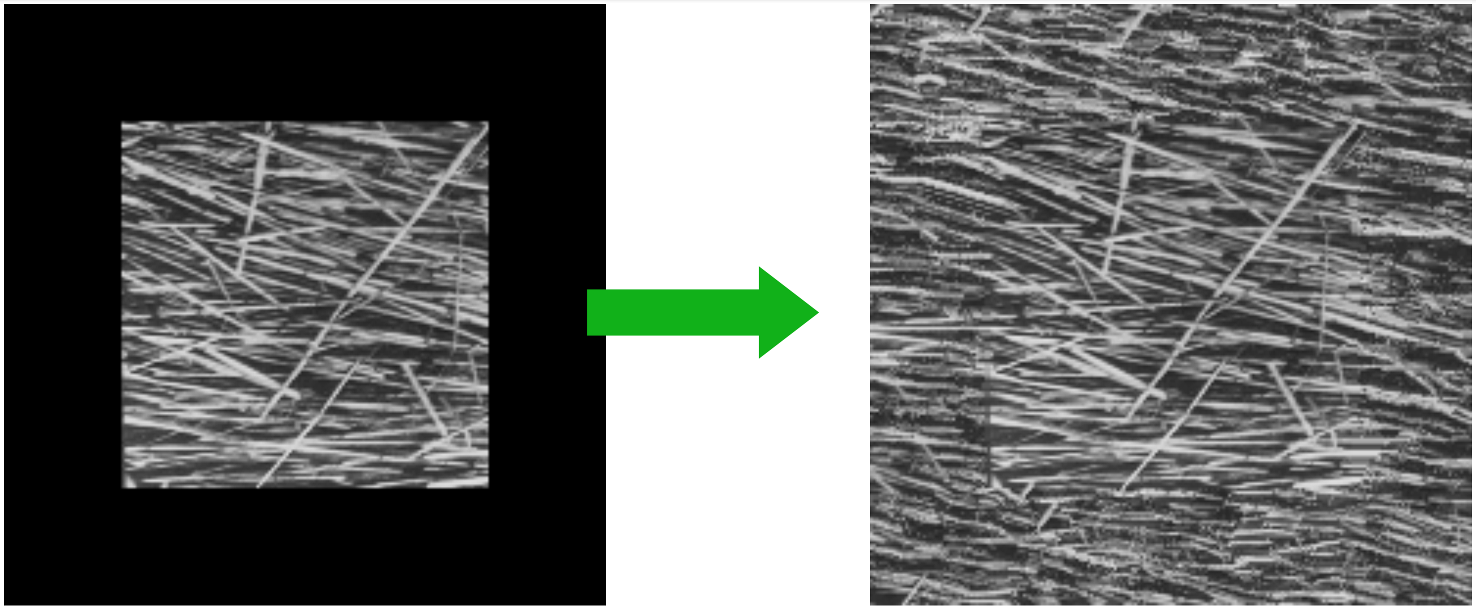
- Fill pixels in “onion skin” order
  - Within each “layer”, pixels with most neighbors are synthesized first
  - Normalize error by the number of known pixels
  - If no close match can be found, the pixel is not synthesized until the end

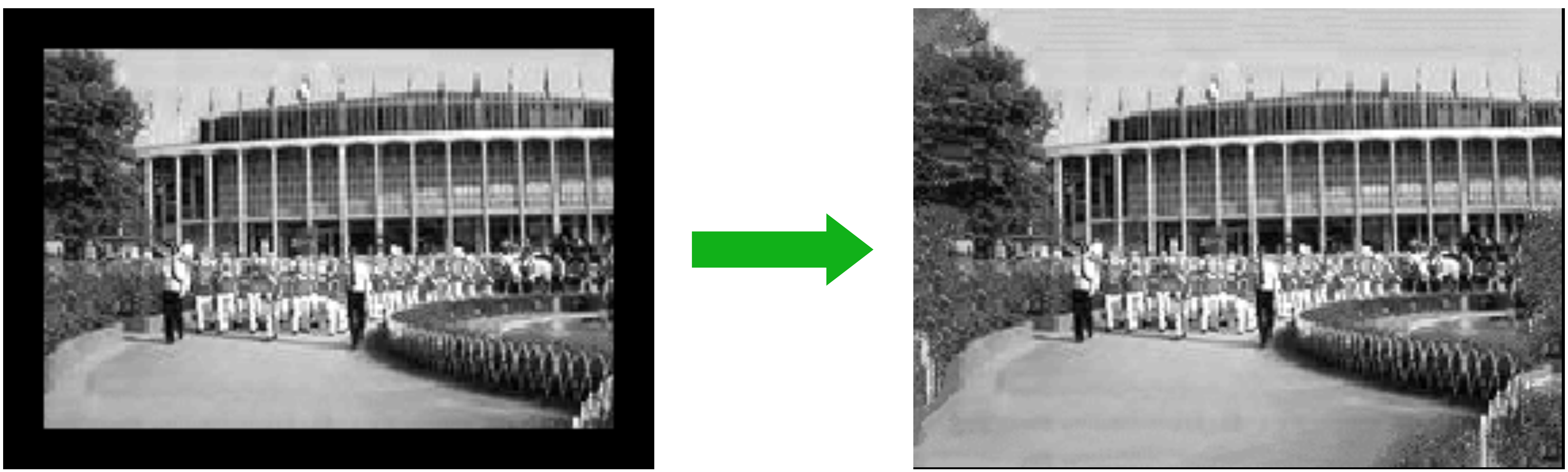
Hole Filling



Efros

Extrapolation





Special video

https://www.youtube.com/watch?v=XlnbNFW2tX8

(Grace Hopper Conference 2017 keynote by Prof. Fei-Fei Li)