TEXTURE ANALYSIS

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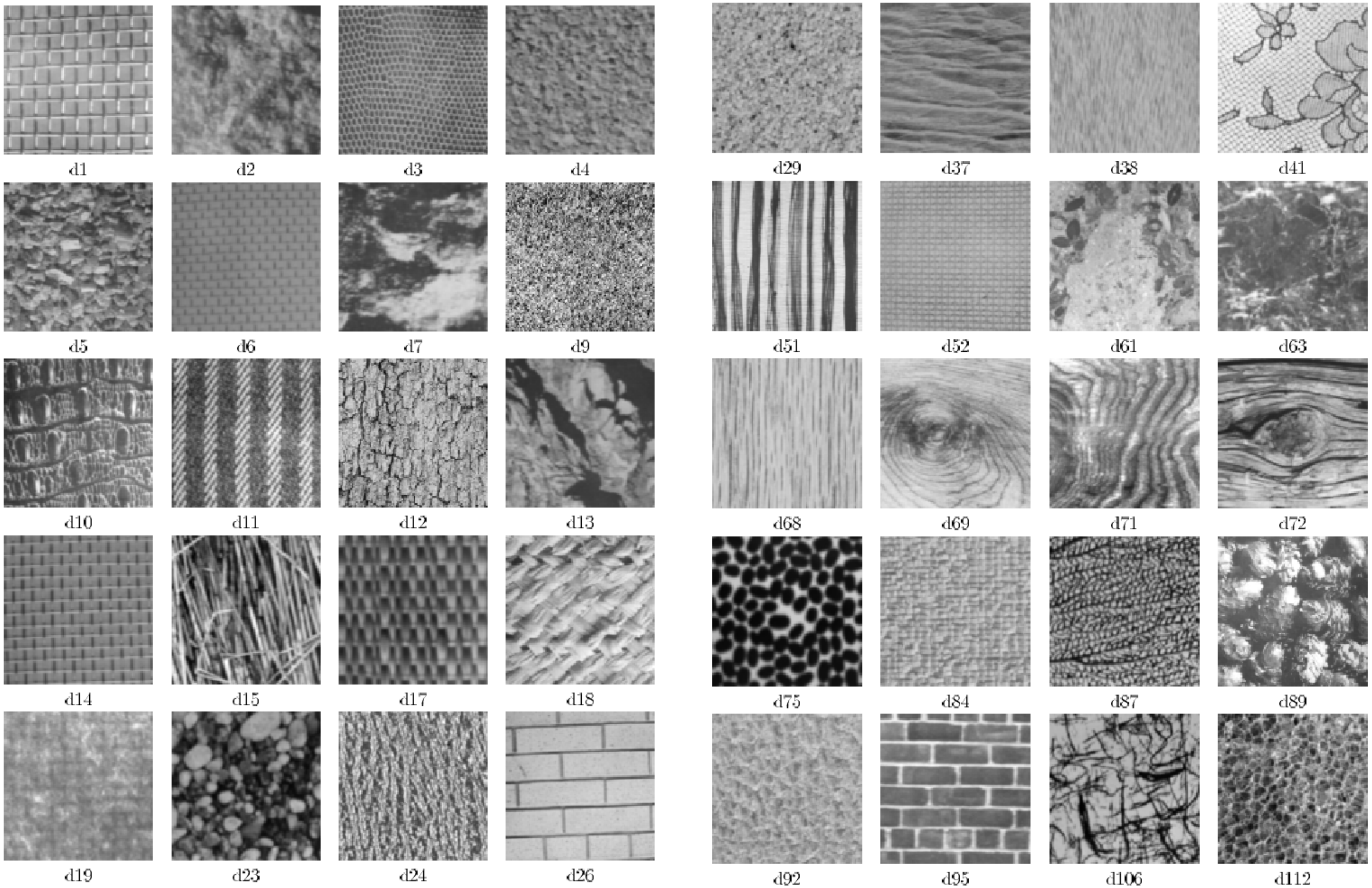
Index

- What is a texture in an image?
- Discriminative textures and pre-attentivity
- Computational methods
  - Gaussian Filters
  - LBP
- Applications

What textures do you know?!

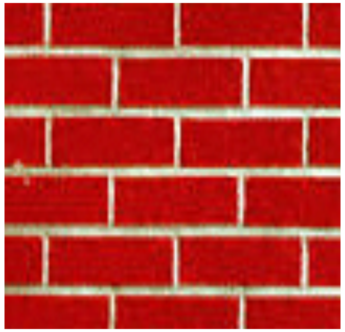
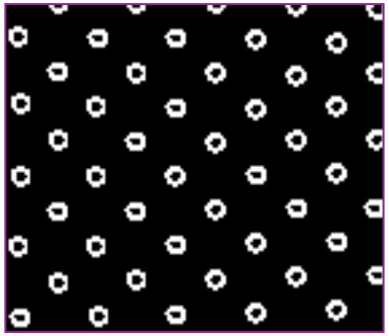
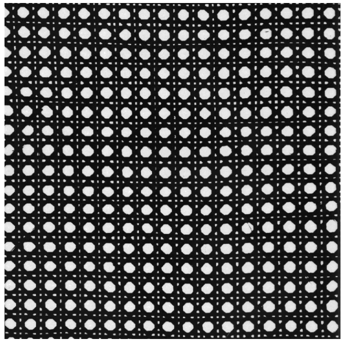
What does define a texture?

What textures do you know?!



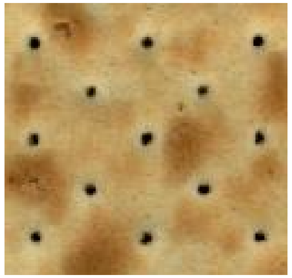
P. Brodatz. *Textures: A Photographic Album for Artists and Designers.* Dover, NY, 1966

Includes: more regular patterns

Includes: more random patterns

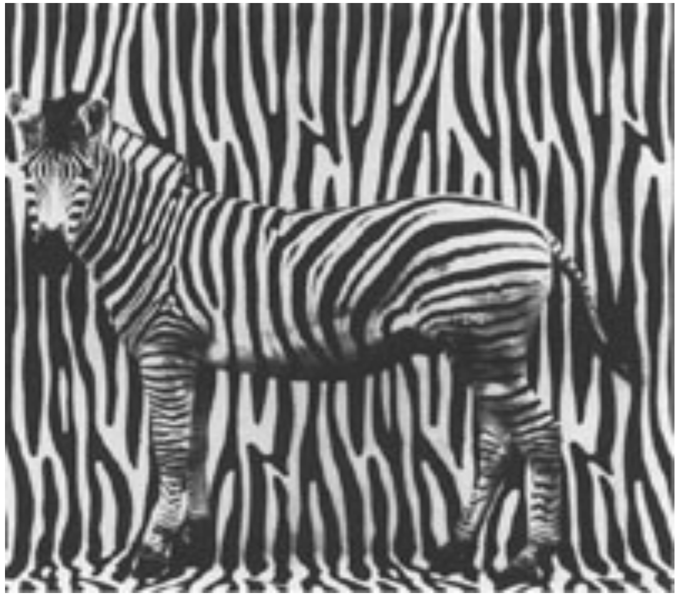


Why shell we use texture analysis?

Automatic analysis and perception of textures

- Image classification
- Image Segmentation
- Object recognition
- Perception of surface orientation, etc.



What applications can be defined for the texture analysis?

Defect Inspection
- textile
- cork
- Wooden furniture
- ceramic
- skin

Analysis of scenes

Improved images and photos
- Printers, cameras

Texture syntesis

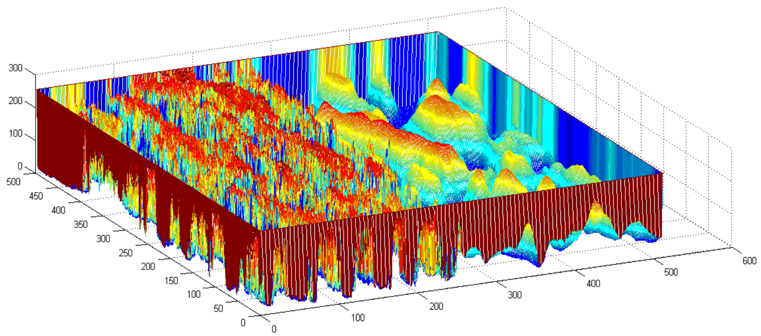
What is a texture?

Visual texture - when the uniformity of the region is perceived as a series of variations in the intensity.

Causes of the visual texture appearance:

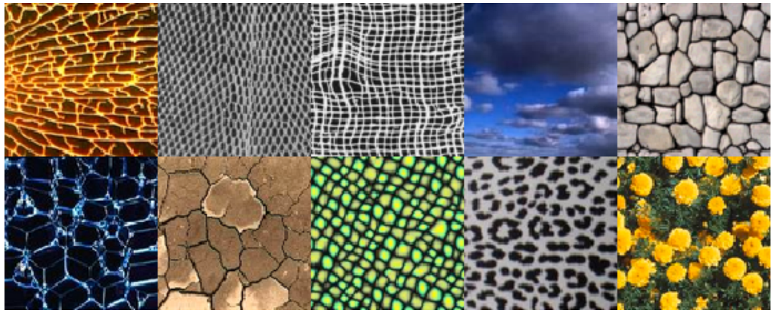
- Changes in reflectance.
- Changes in the micro-orientation of a surface.

Relevance: source of information about the scene, useful for certain visual processes (segmentation and perception of orientation).



Types of textures

Examples of natural textures.



Examples of weakly-homogeneous textures.

Examples of artificial regular textures.

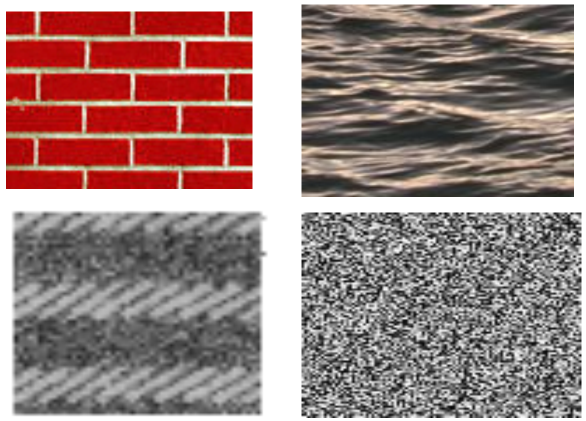
Examples of stochastic textures.

What is a texture?

- Types: many, it depends on the criteria: structured, unstructured, etc.

- **Three general groups**:
  - structured,
  - stochastic and
  - mixed.

- How are they formed?



Repetitive or structured pattern

Stochastic patterm

A mix of both

When a texture is distinguishable even if it has the same lighting, color and contrast?

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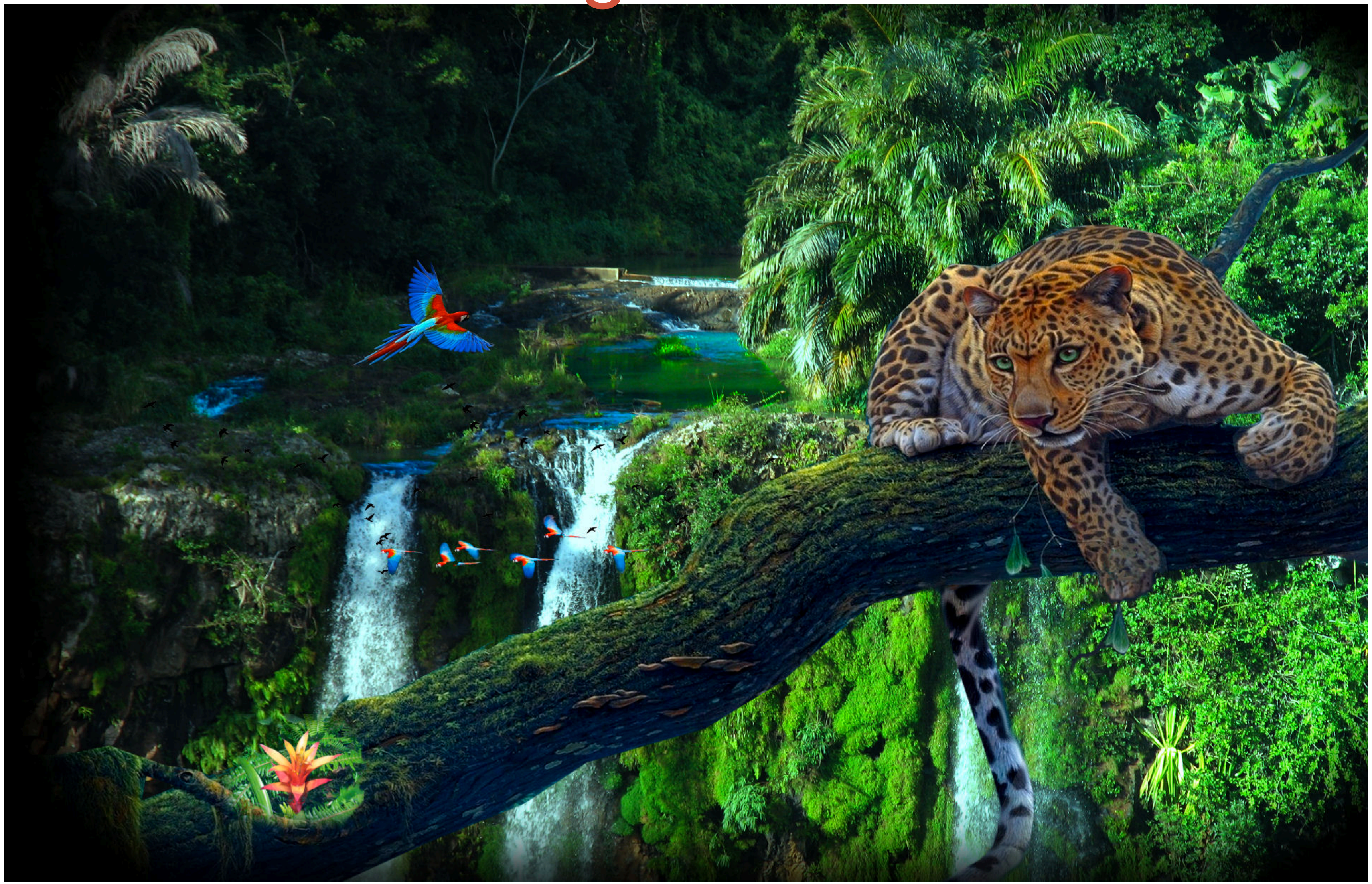
Discriminating texture

What kind of response will we get with an edge detector for these images?

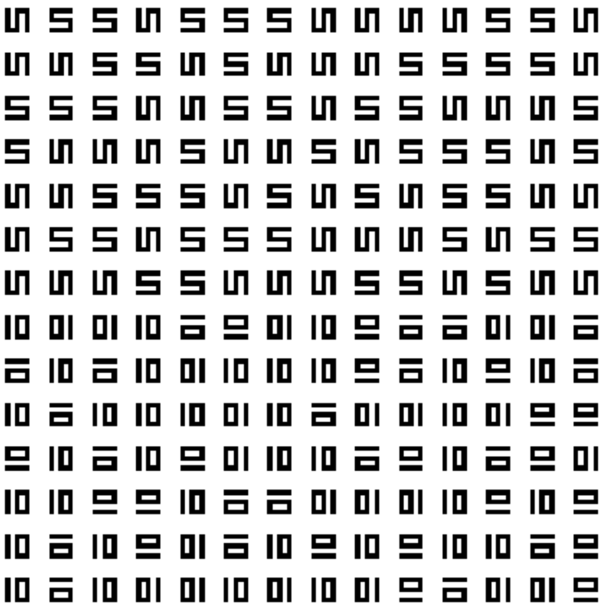
Images from Malik and Perona, 1990

Discriminating texture

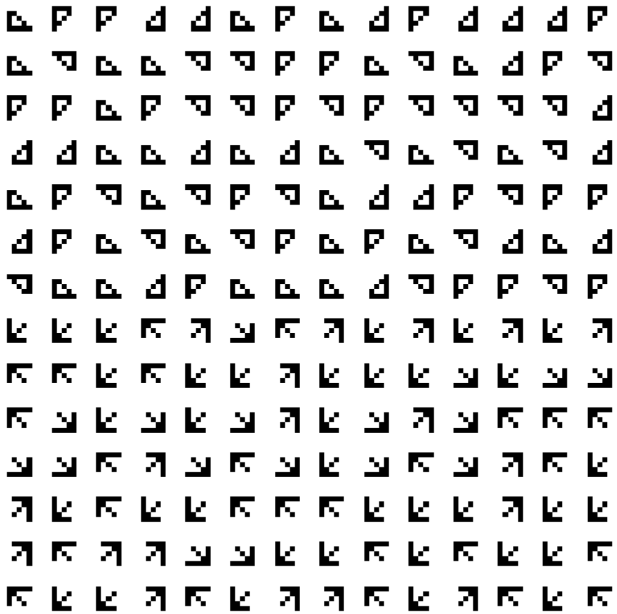


…and for this image?

Texture discrimination and pre-attentivity



Texture pre-attentively
not distinguishable.



Pre-attentively
distinguishable texture.

Textures are said to be **pre-attentively discriminable** if we can discriminate them in a time interval small enough (less than 100ms):

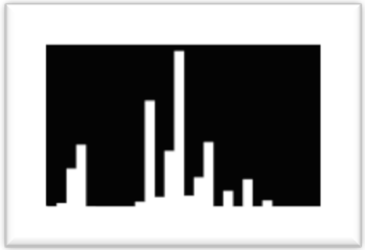
- that does not allow detailed visual analysis of all areas of the image.

Texture discrimination and preattentivity

Bela Julesz: psychophysical theory on textons proposed to explain the perception of textures (1983).

Theory: The pre-attentive discrimination of textures is based on the statistical processing of the images.

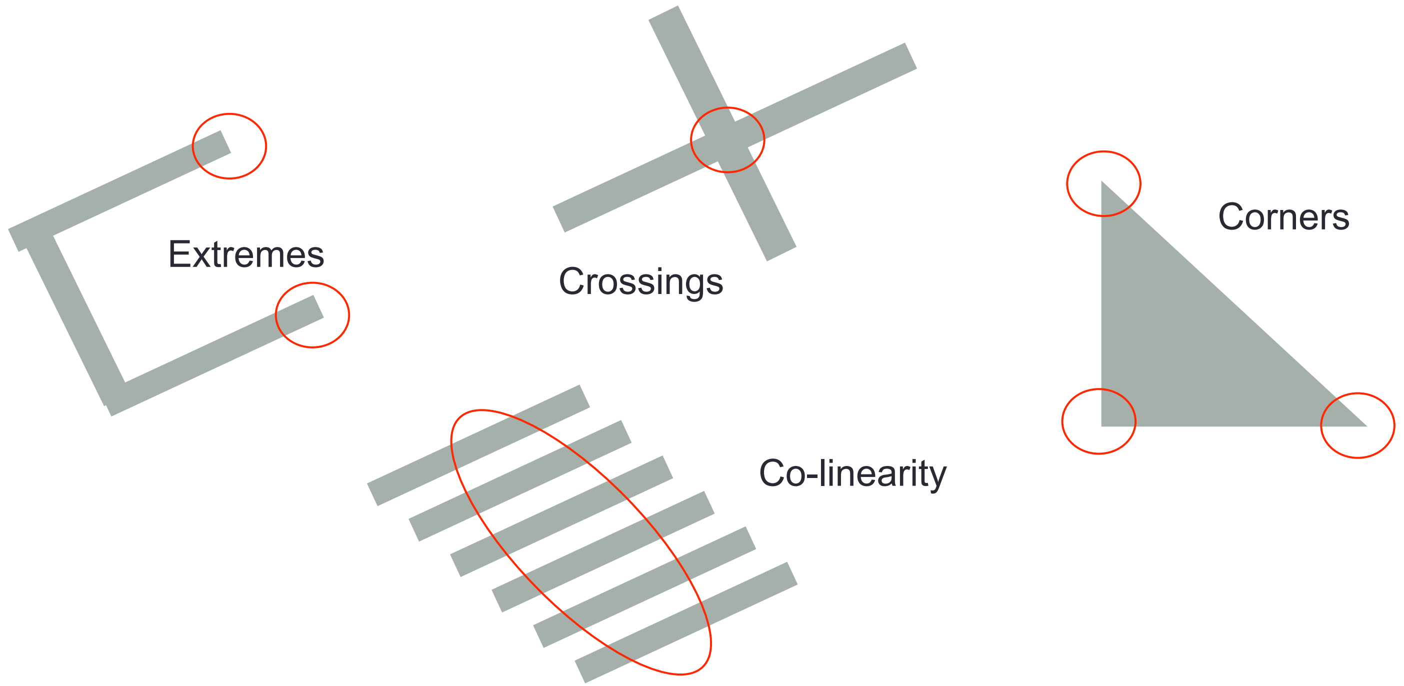
1st order statistics: probability or likelihood of having given intensity value at a certain point (can be calculated from the histogram, i.e. the average value of the image).



2nd order statistics: probability of a certain combination of gray levels at the extremes of segments (associated to pairs of points).

Texture discrimination and pre-attentivity

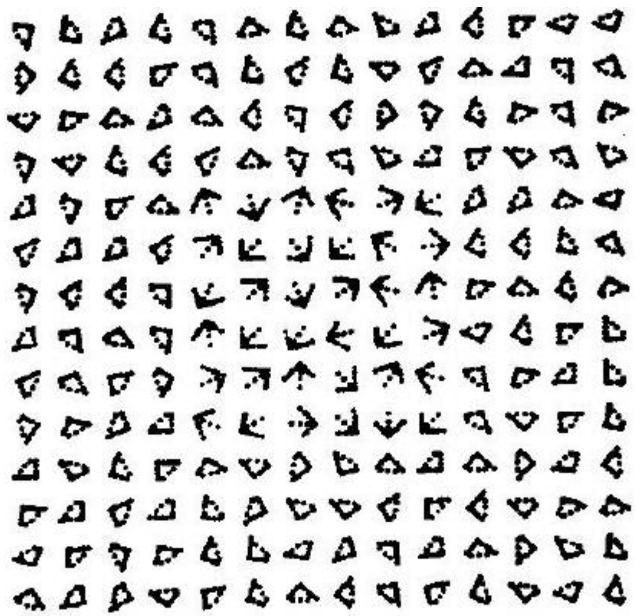
What is the 2nd order statistics in structural textures?

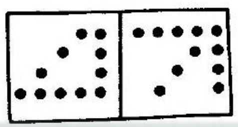


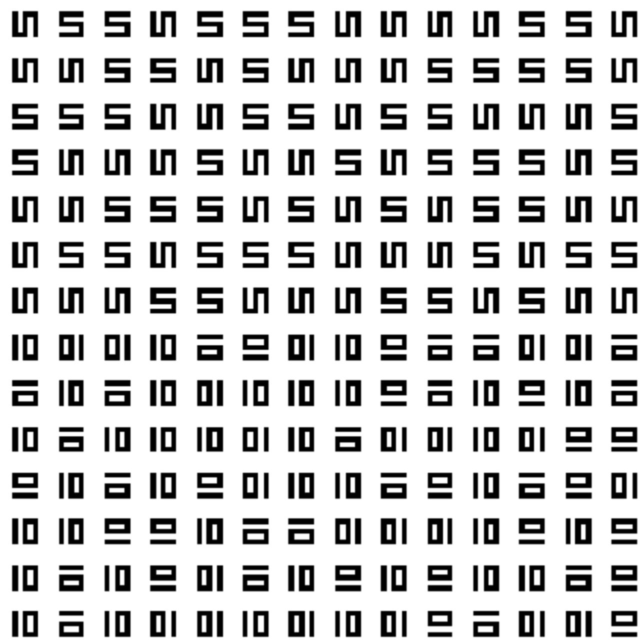
Textons (Julesz, 1983) - visual characteristics of the image that are used in the perception of texture – extremes, crossings, corners and co-linearity**.**

Texture discrimination and pre-attentivity

Textons







No statistical difference of 1st order in the textons, but in 2nd one - yes!

Same 2nd order textures are not pre-attentively discriminable!

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Computational methods for texture discrimination

Assumptions

Texture (stochastic and structural) is a property of regions:

- contextual property;

- description of the distribution of gray levels in regions more or less extensive.

The texture can be perceived at different scales or levels of resolution.

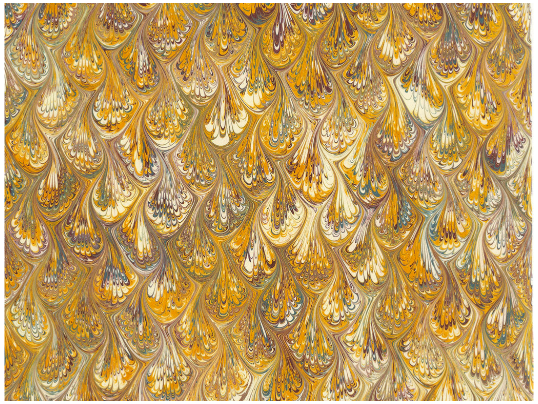
A region presents a texture when the number of primitive patterns is large (not easily countable).

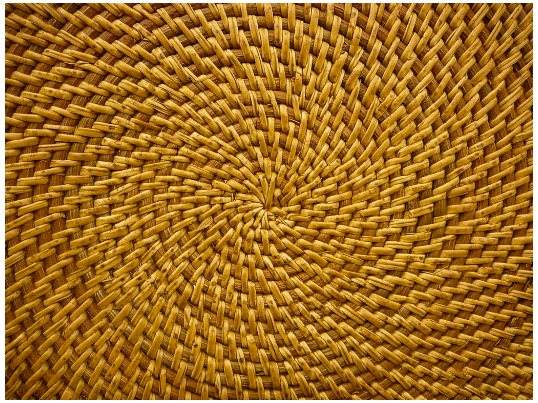
Texture representation

Assumptions

- Consider textures as made up of repeated local patterns, so:

  1. Find the patterns
     - Use filters that look like patterns (spots, bars, raw patches…)
     - Consider magnitude of response





  2. Describe their statistics within each local window
     - Mean, standard deviation
     - Histogram
     - Histogram of “prototypical” feature occurrences (textons)

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Texture representation

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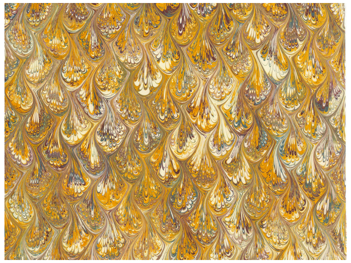

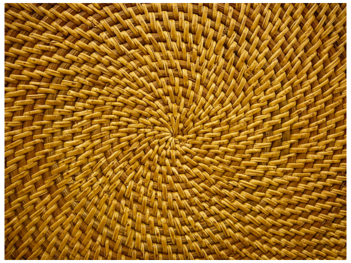

  2. Describe their statistics within each local window
     - Mean, standard deviation
     - Histogram
     - Histogram of “prototypical” feature occurrences (textons)

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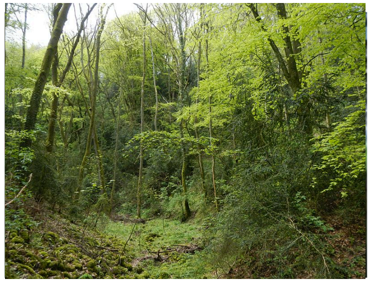
What kind of filters to use?




Buildings






Forest




Sunset

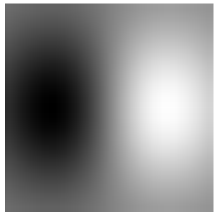
Different textures have different attributes -> we need different filters!

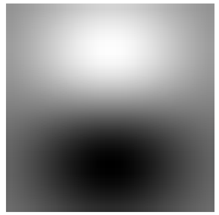
Recall

- We looked for edges convolving with filters like:

Sobel: $M_x = \begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline\end{array}$; $M_y = \begin{array}{|c|c|c|}\hline 1 & 2 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -2 & -1 \\ \hline\end{array}$

Derivatives of
of Gaussians

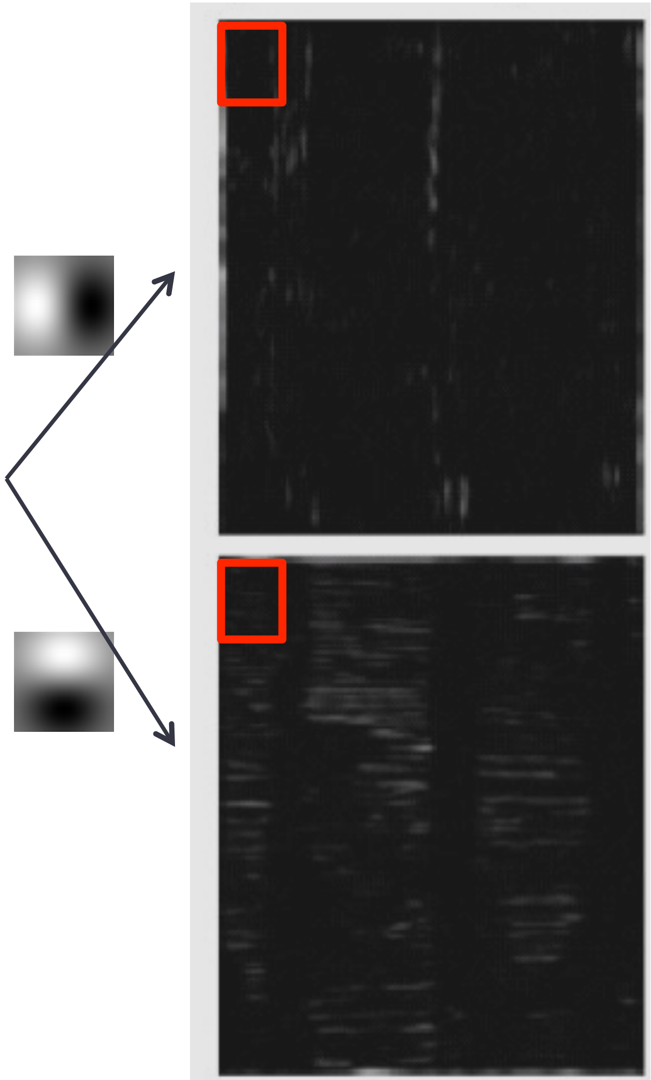




Convolution filters (kernels) are “imitations” of structures we are looking for.

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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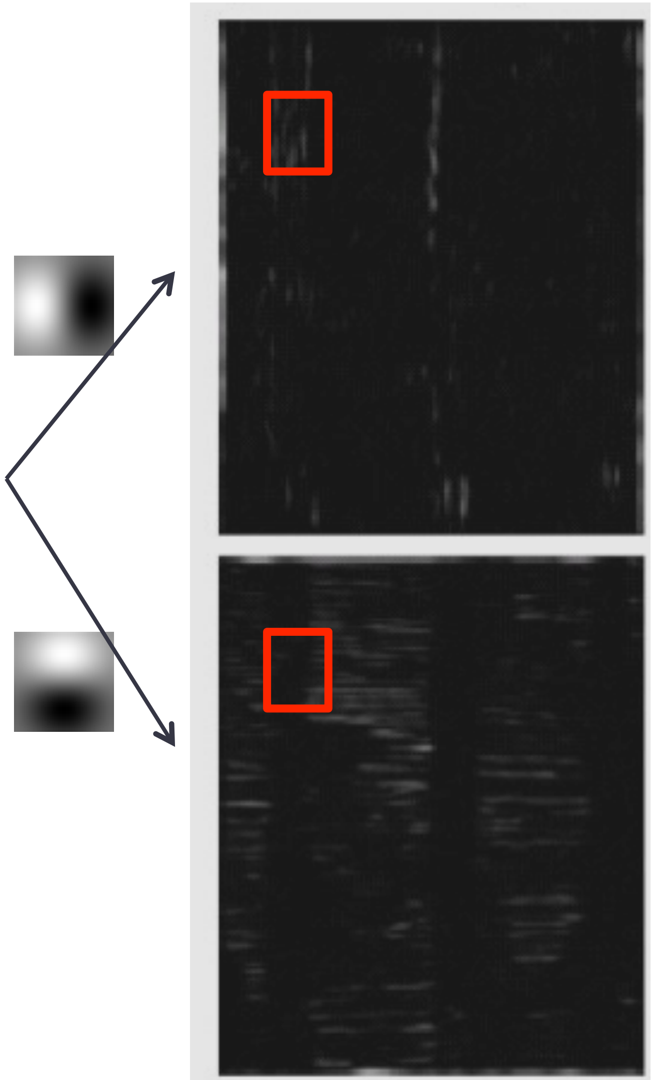
Texture representation: example

original image



derivative filter responses, squared

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

⋮

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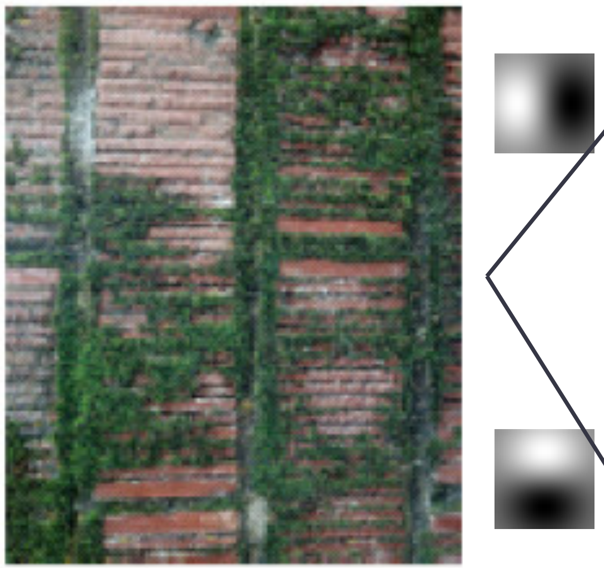
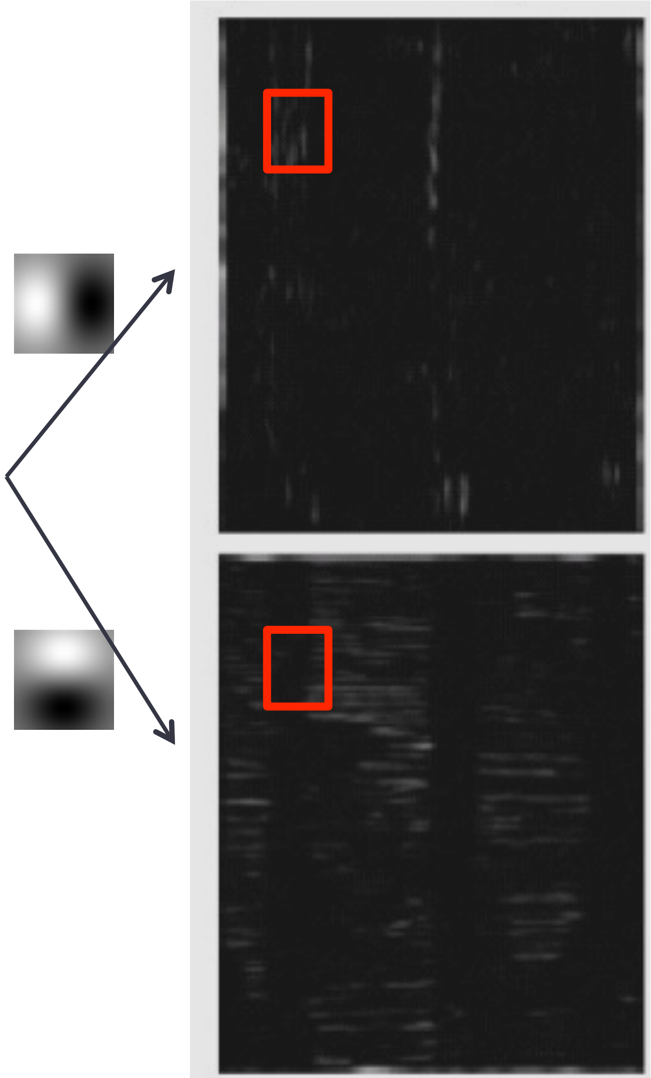
Texture representation: example



original image



derivative filter responses, squared

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Win. #1	4	10
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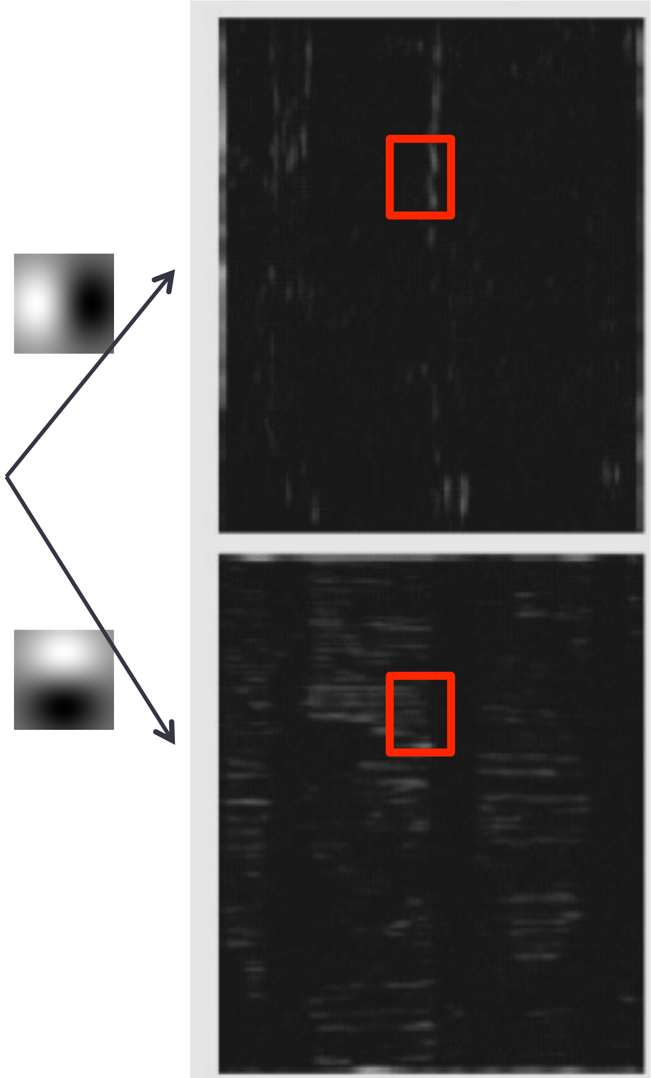
Texture representation: example

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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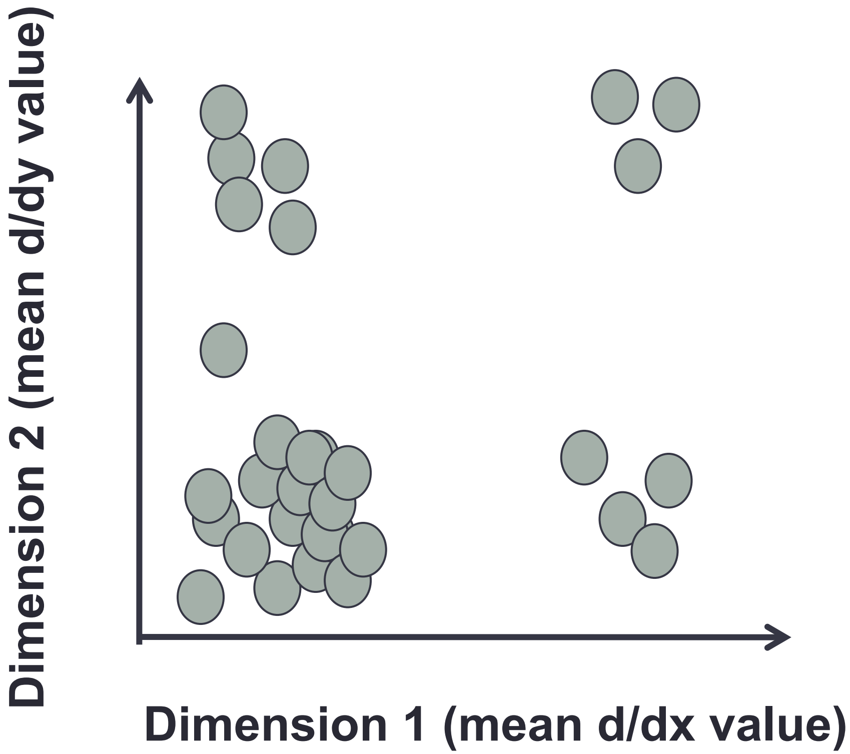
Texture representation: example



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

⋮

statistics to summarize patterns in small windows

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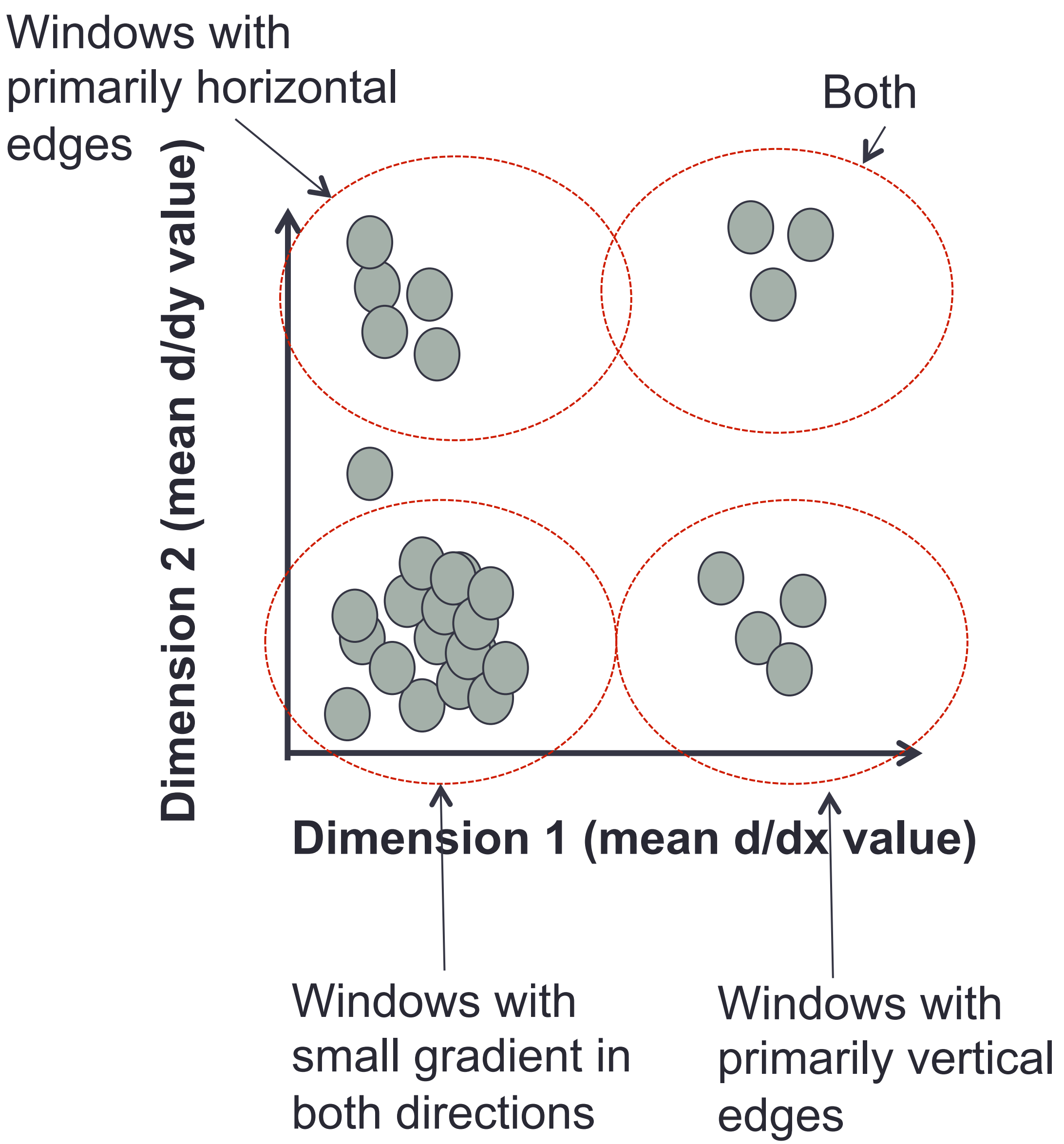
Texture representation: example



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

⋮

statistics to summarize patterns in small windows

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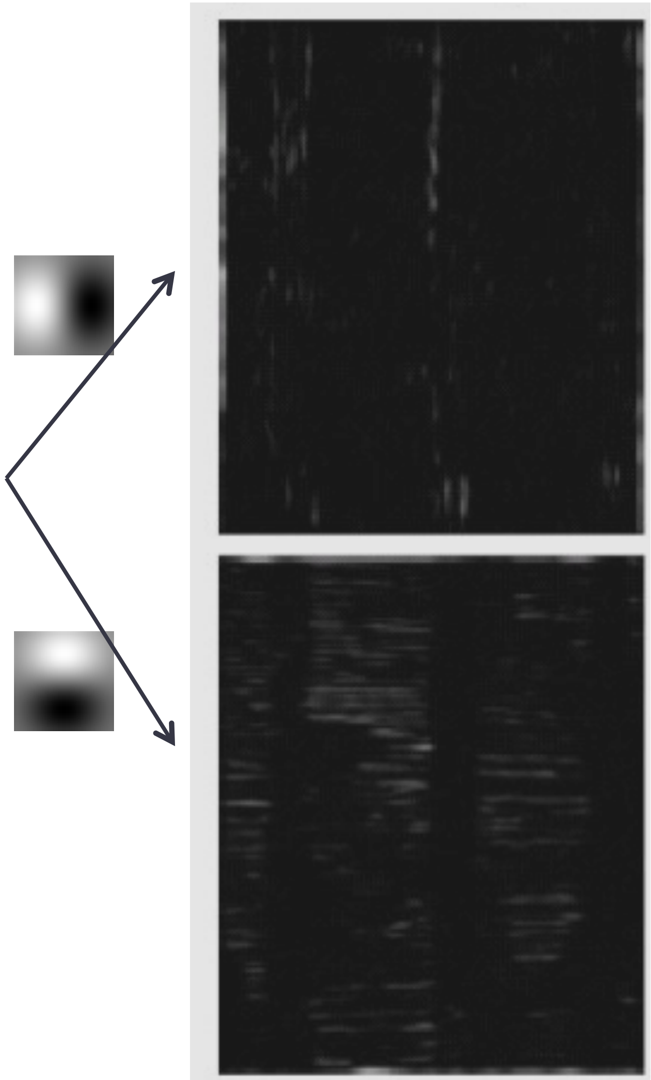
Texture representation: example

original image



derivative filter responses, squared

visualization of the assignment to texture "types"

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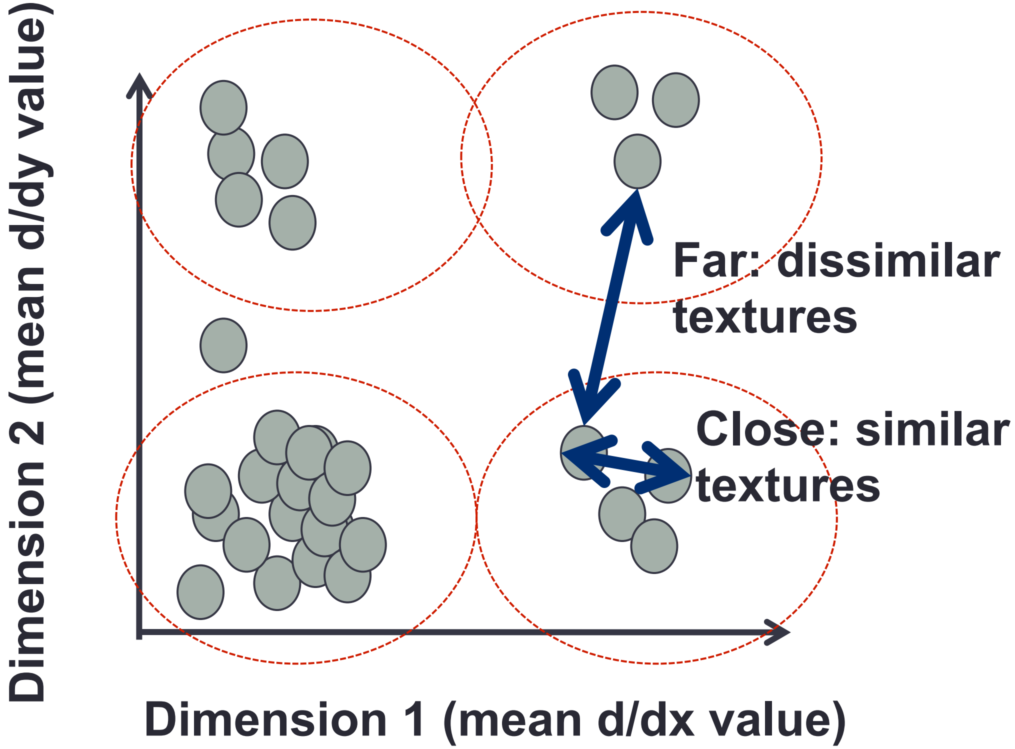
Texture representation: example



	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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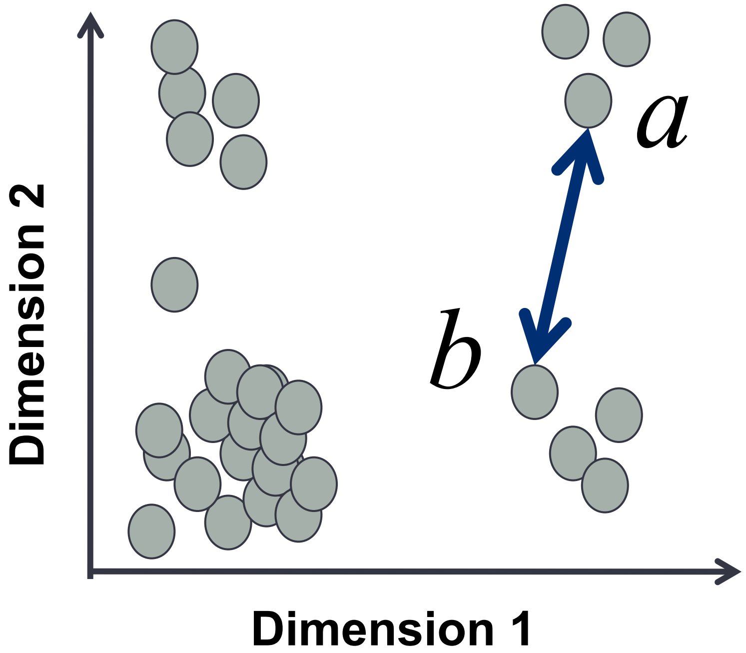
Texture representation: example



$$D(a,b) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2}$$

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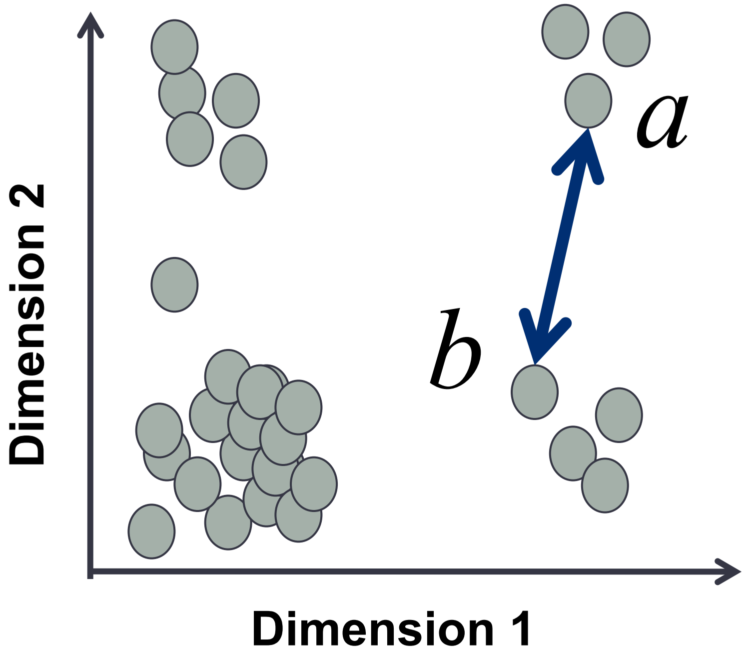
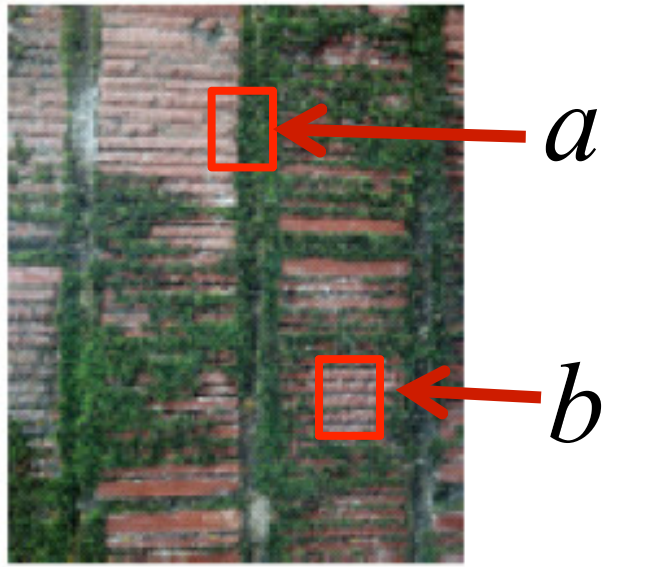
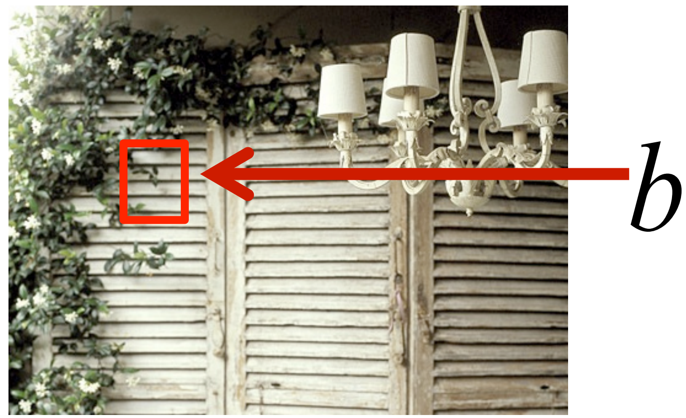
Texture representation: example







Distance reveals how dissimilar texture from window a is from texture in window b.

If the whole image contains the same texture, what would be the feature space representation looks like?

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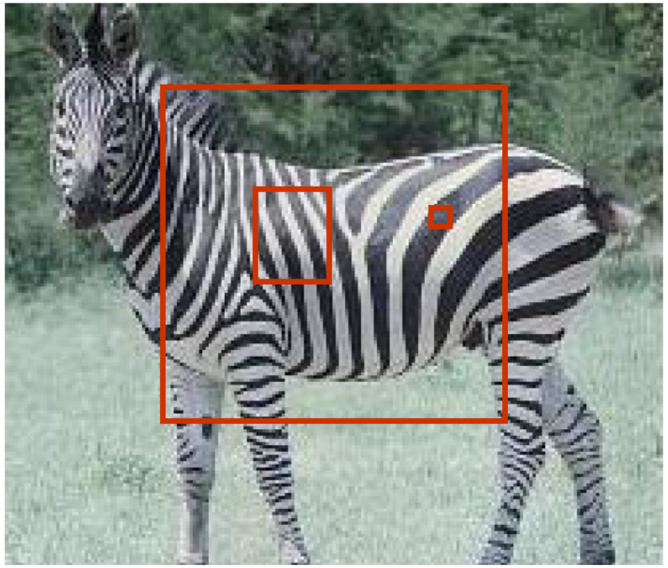
Texture representation: window scale

- We're assuming we know the relevant window size for which we collect these statistics.

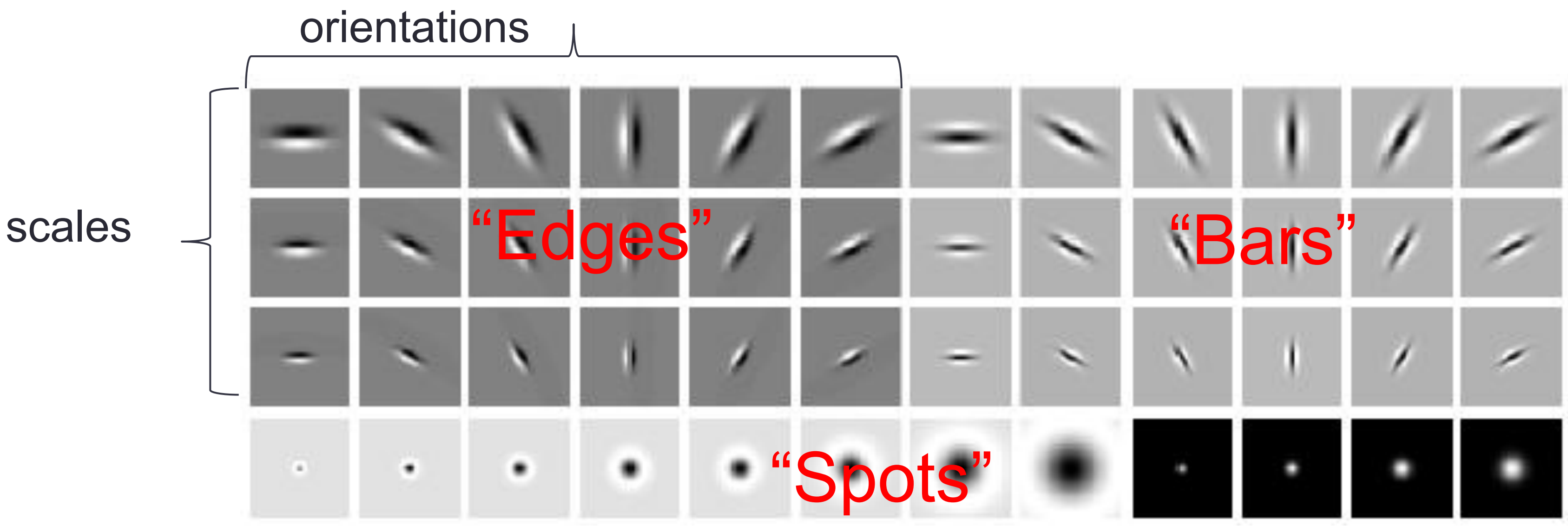


Possible to perform scale selection by looking for window scale where texture description is not changing.

Filter banks

- Our previous example used two filters, and resulted in a 2-dimensional feature vector to describe texture in a window.
  - x and y derivatives revealed something about local structure.
- We can generalize to apply a collection of multiple (*d*) filters: a “filter bank”
- Then our feature vectors will be *d*-dimensional.
  - still can think of nearness, farness in feature space

Filter banks

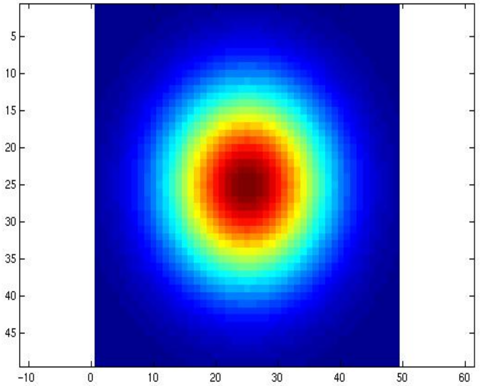


- What filters to put in the bank?
  - Typically, we want a combination of scales and orientations, different types of patterns.

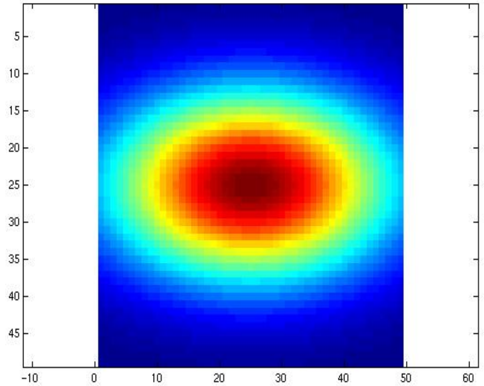
Matlab code available for these examples:
http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

How to generate filters: using a Gaussian function

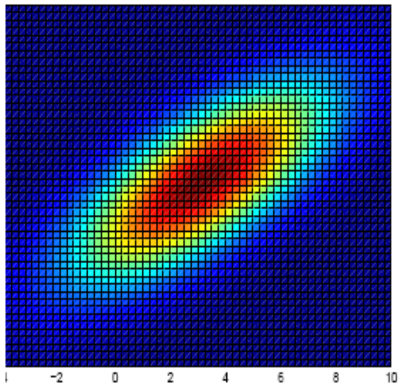
$$p(x;\mu,\Sigma) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right).$$



$$\Sigma = \begin{bmatrix} 9 & 0 \\ 0 & 9 \end{bmatrix}$$



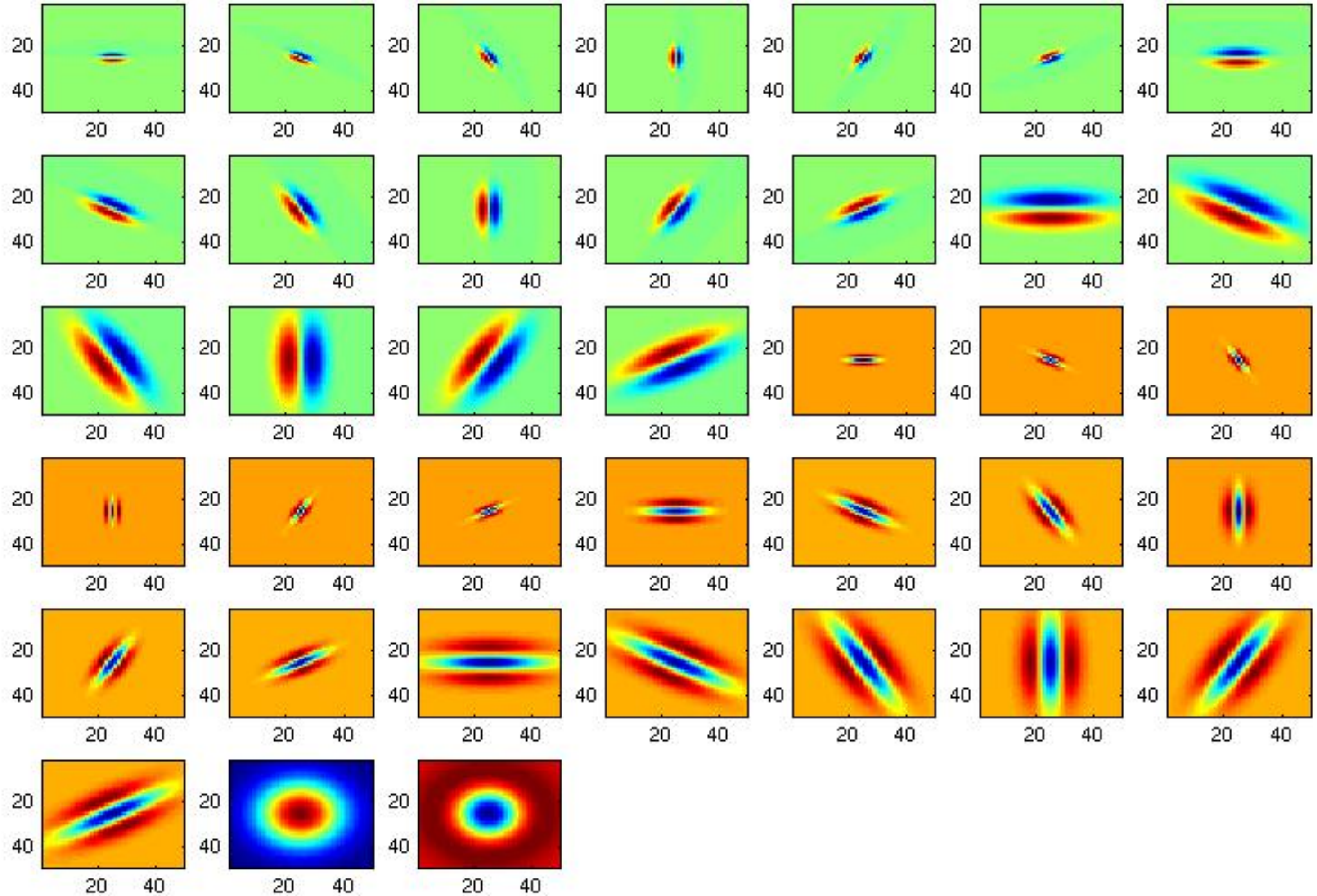
$$\Sigma = \begin{bmatrix} 16 & 0 \\ 0 & 9 \end{bmatrix}$$



$$\Sigma = \begin{bmatrix} 10 & 5 \\ 5 & 5 \end{bmatrix}$$

Matlab code available for these examples:
http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

Filter bank



Matlab code available for these examples:
http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

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

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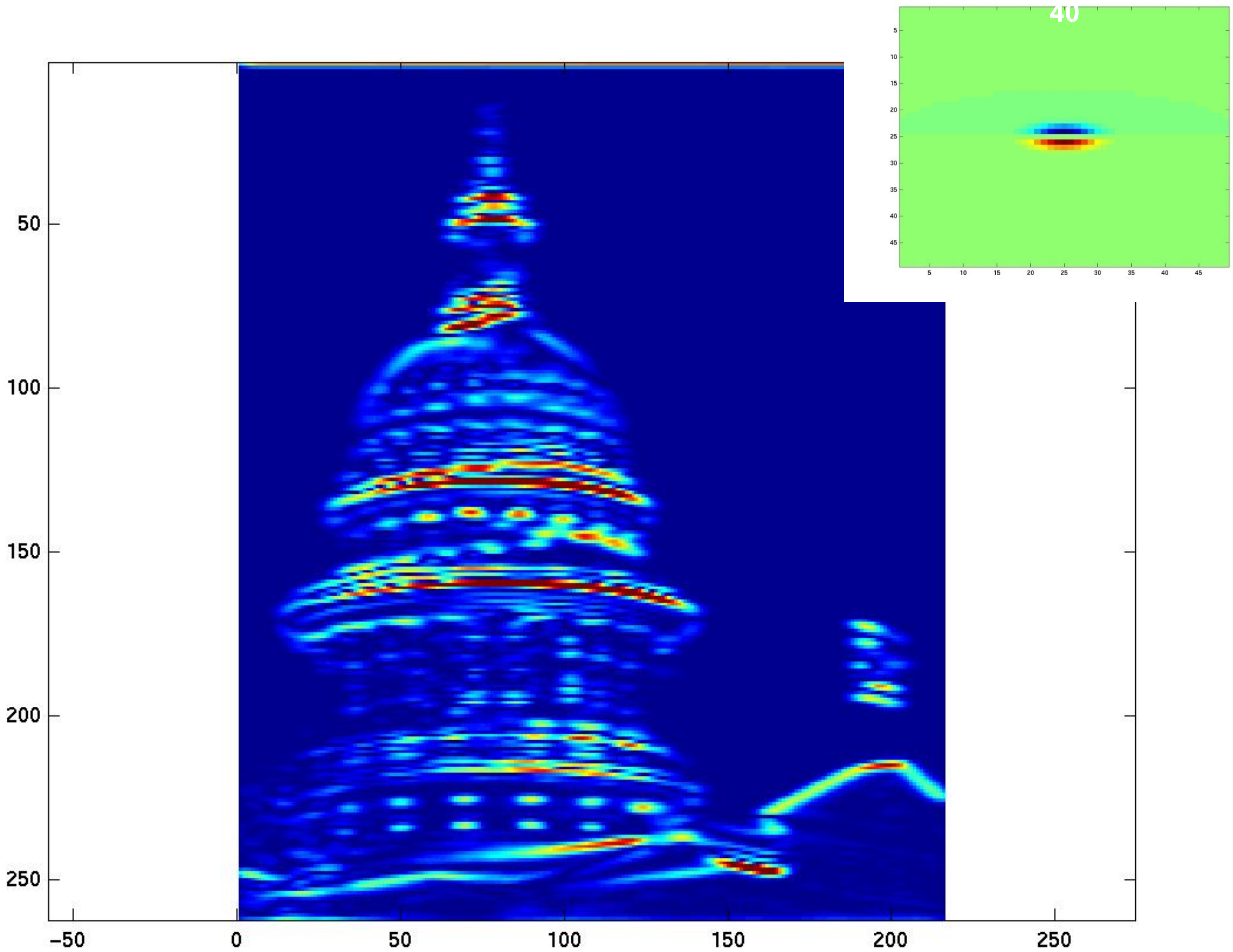

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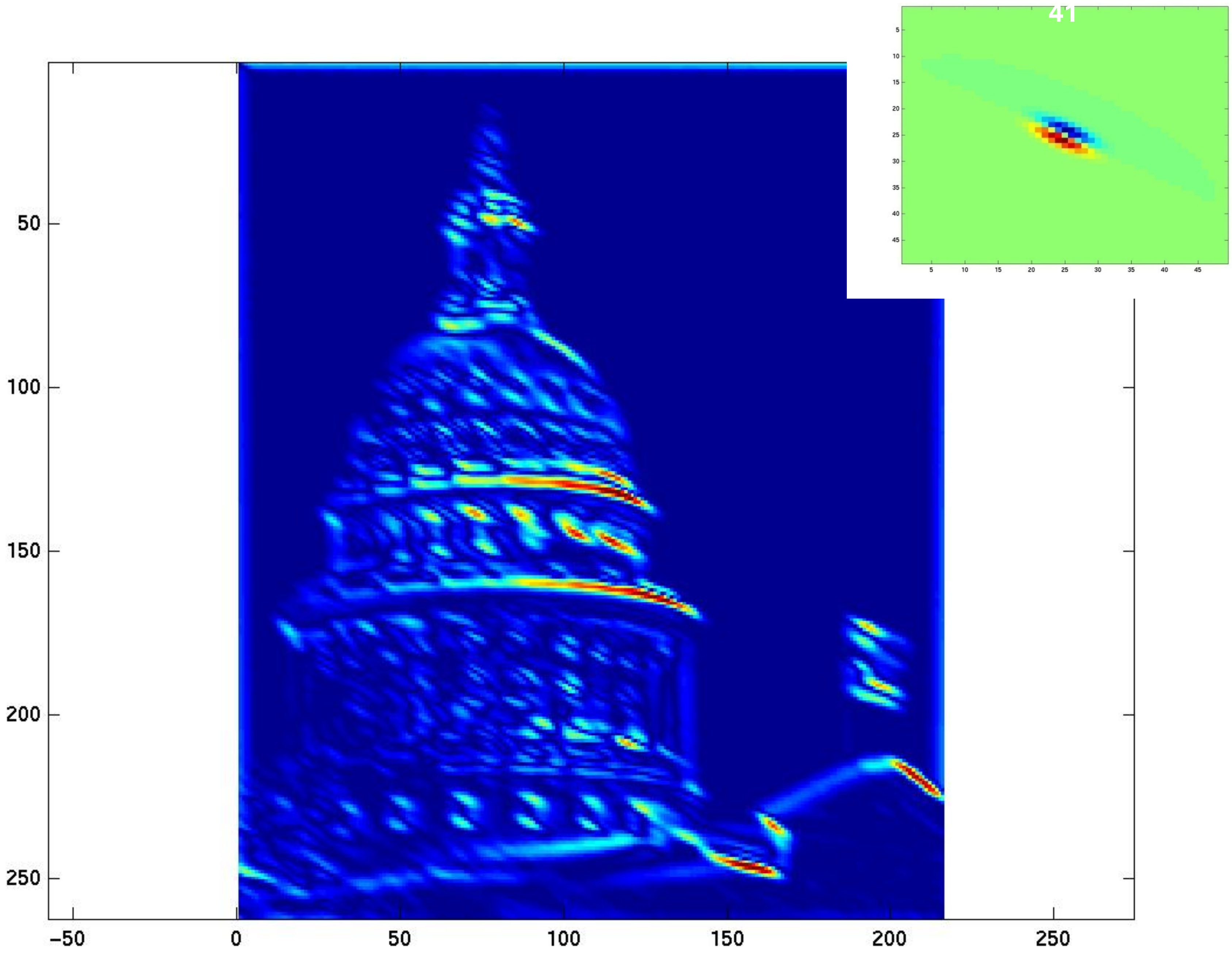

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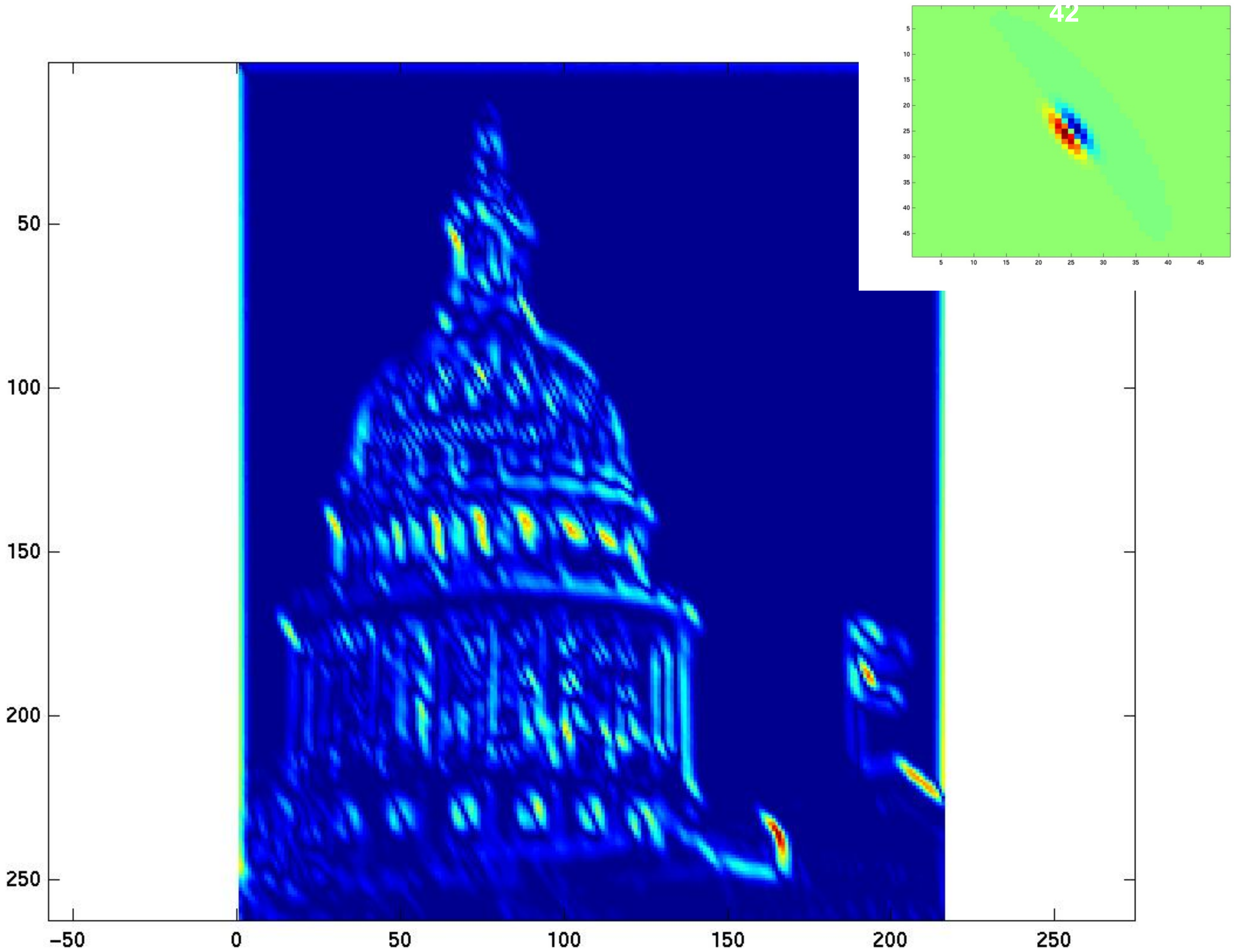

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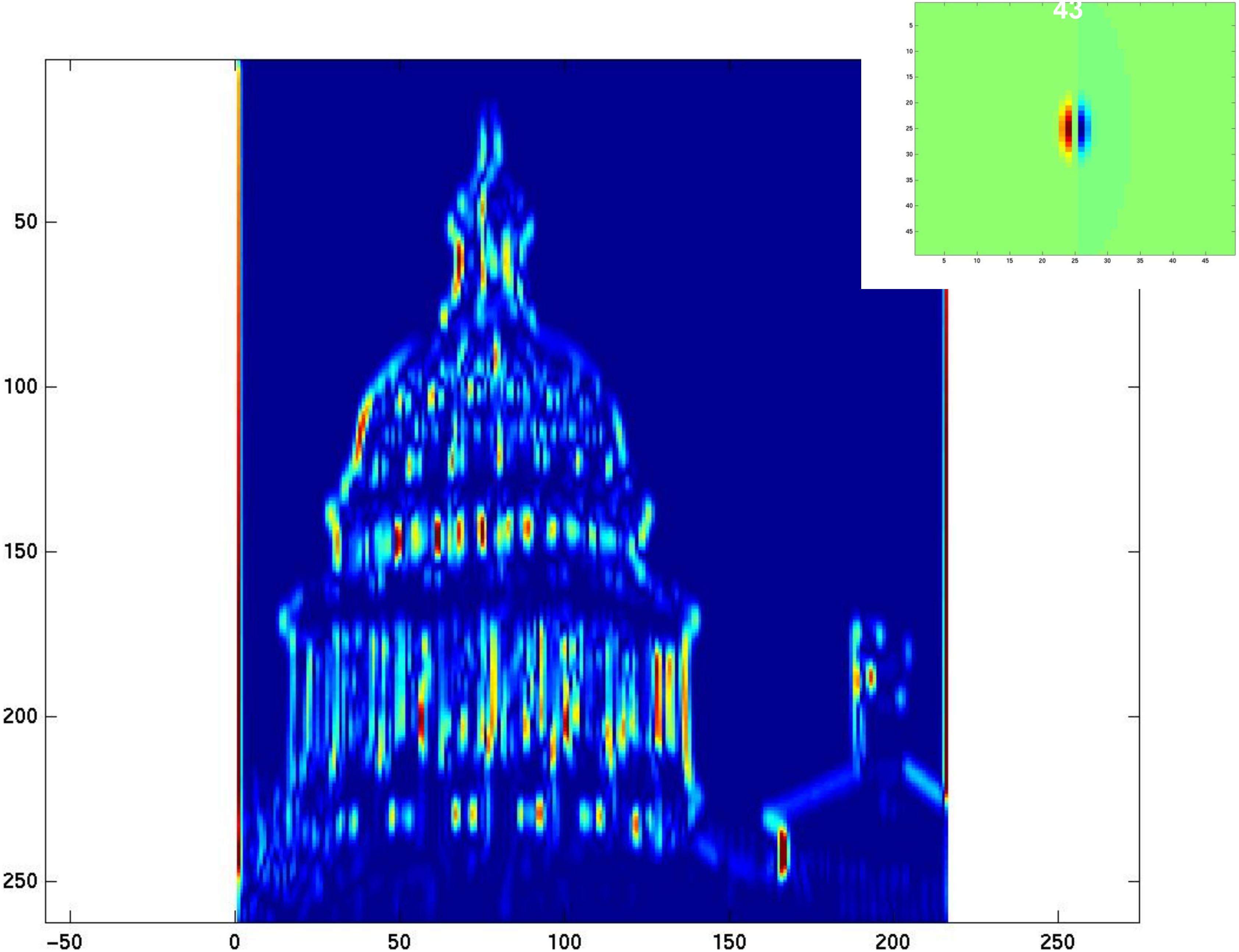

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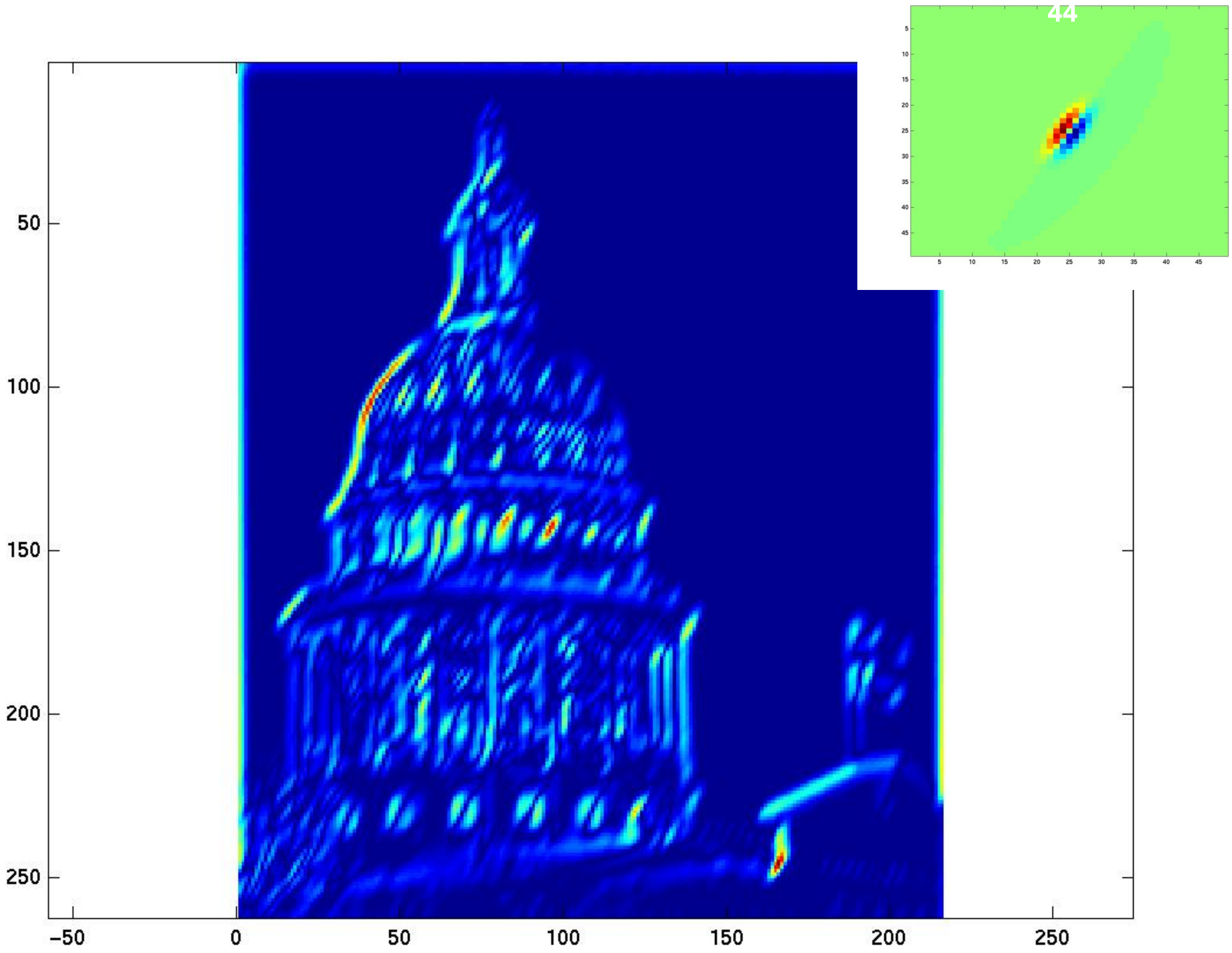

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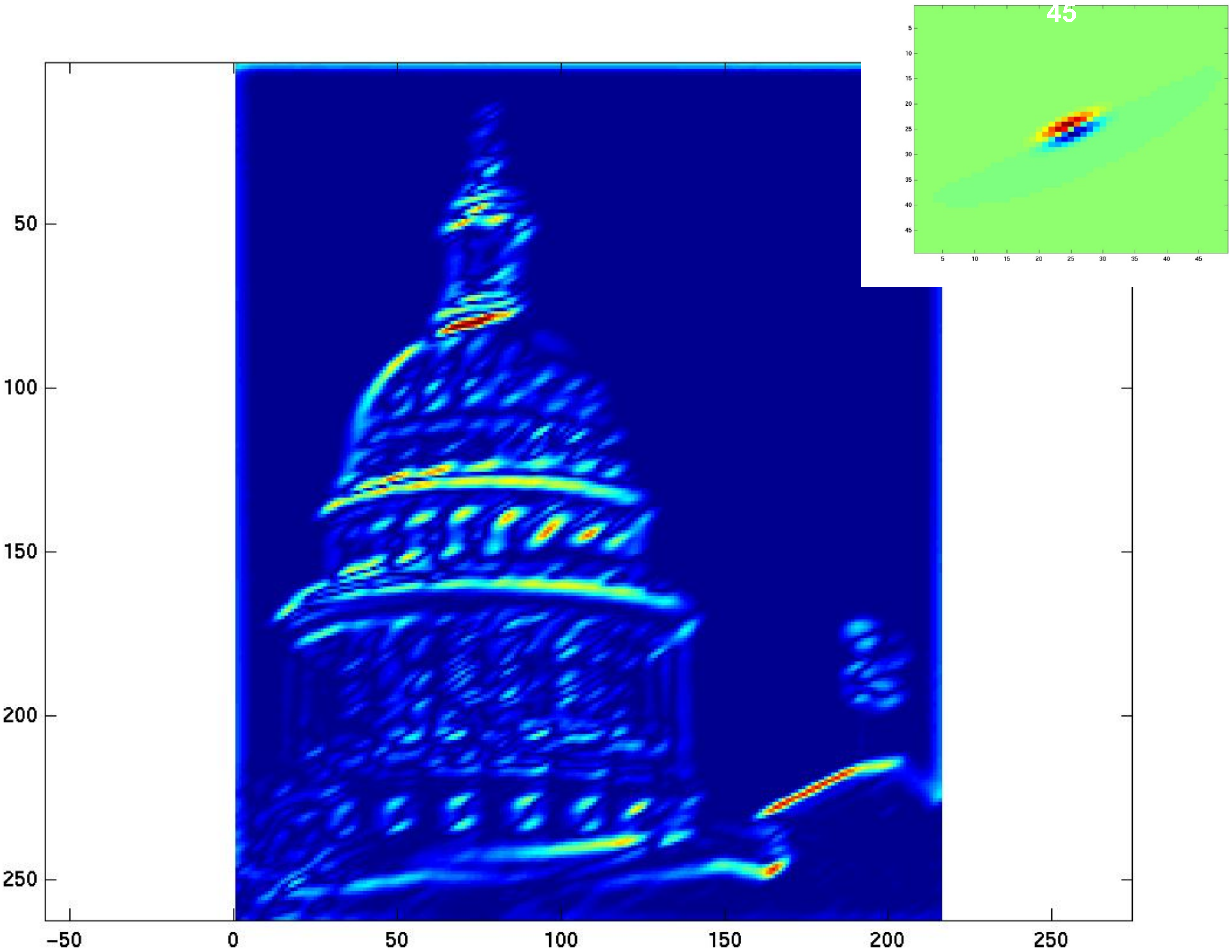

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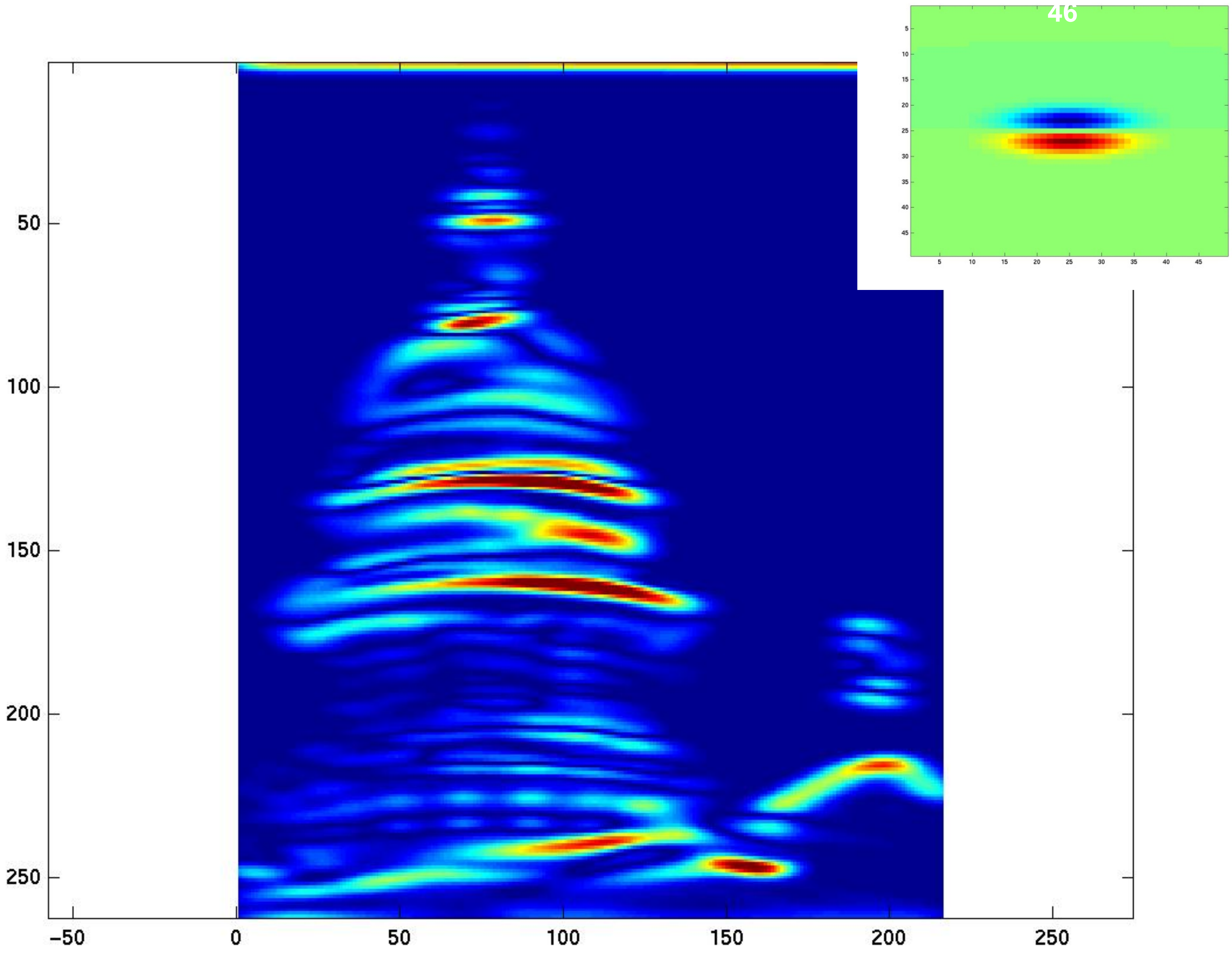

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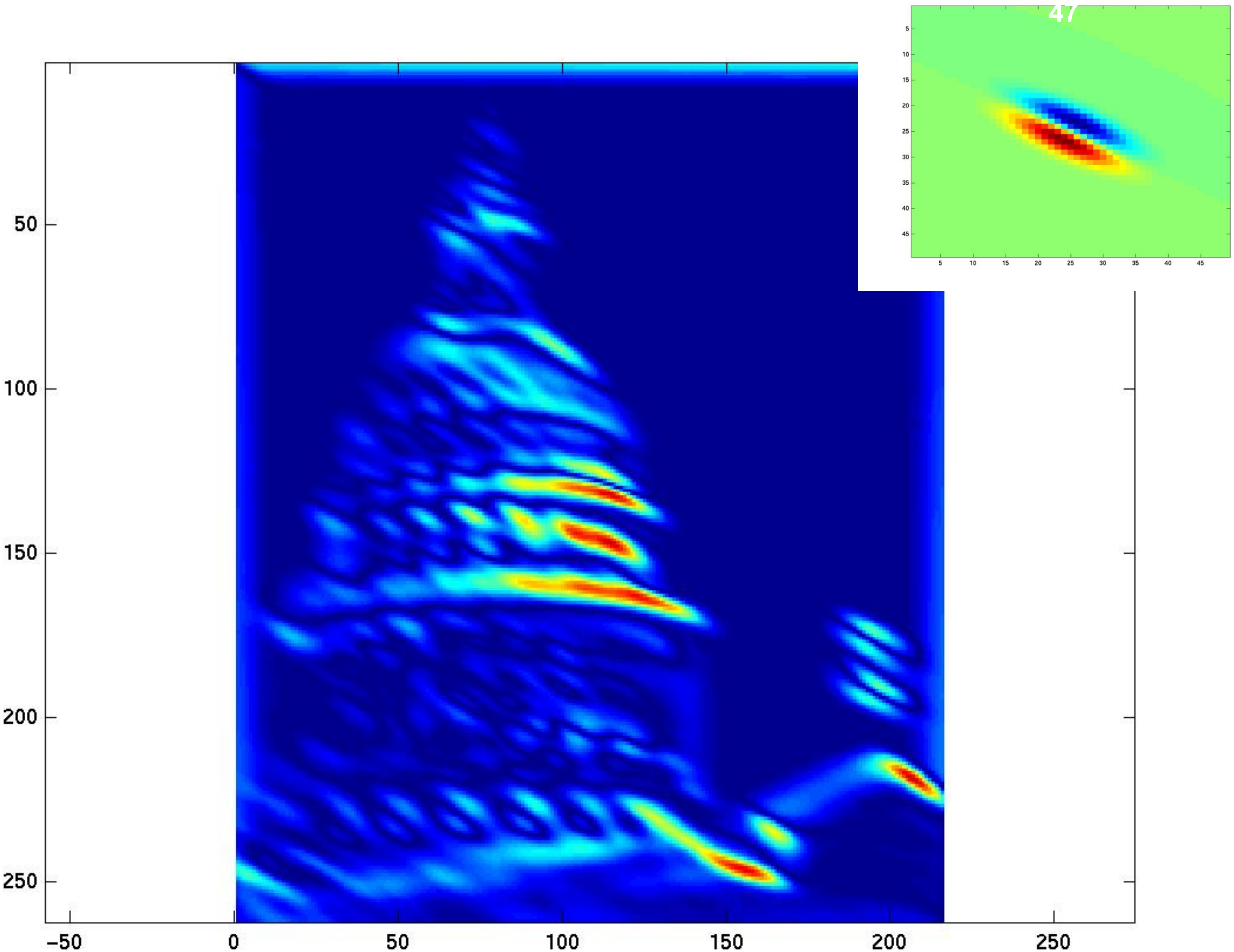

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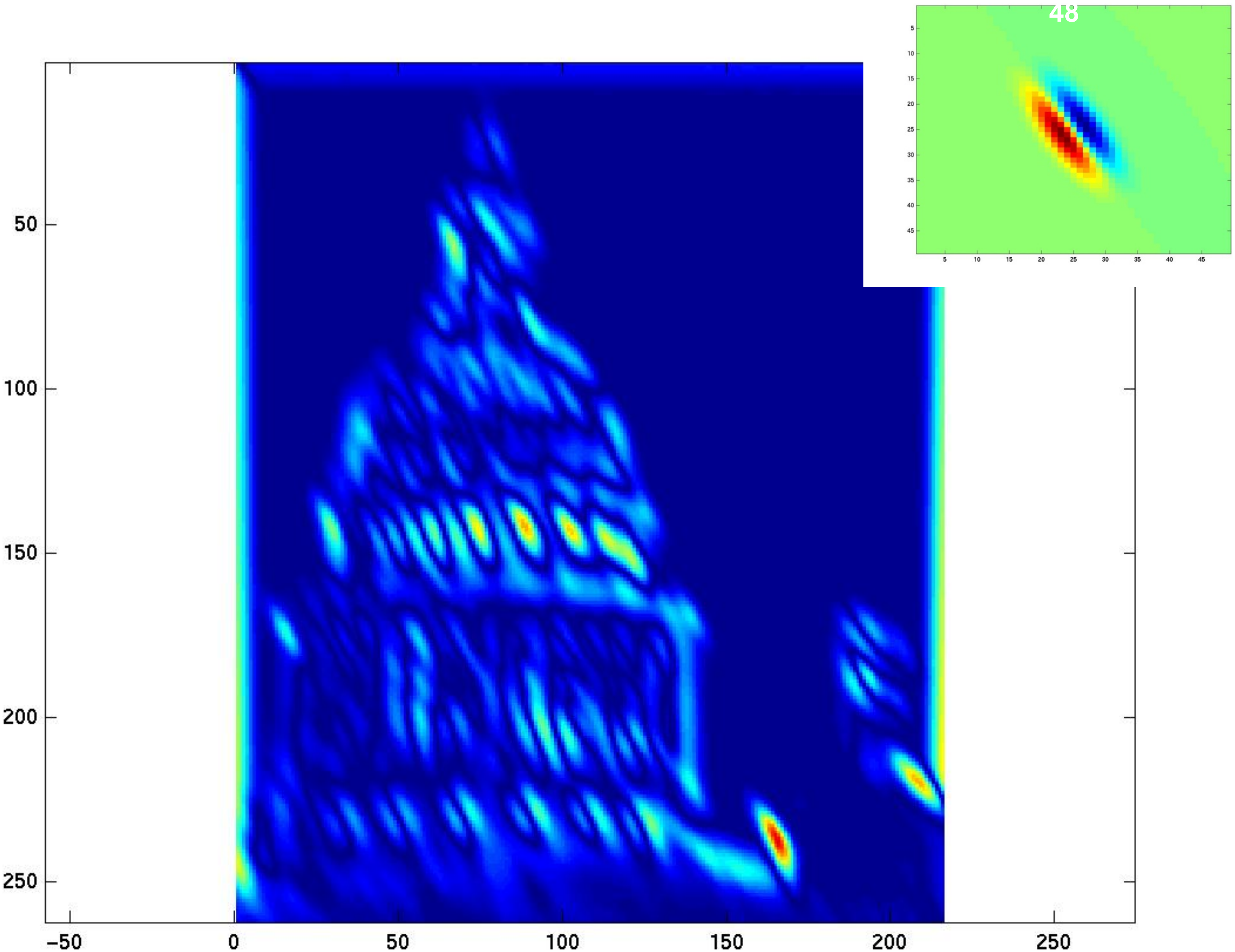

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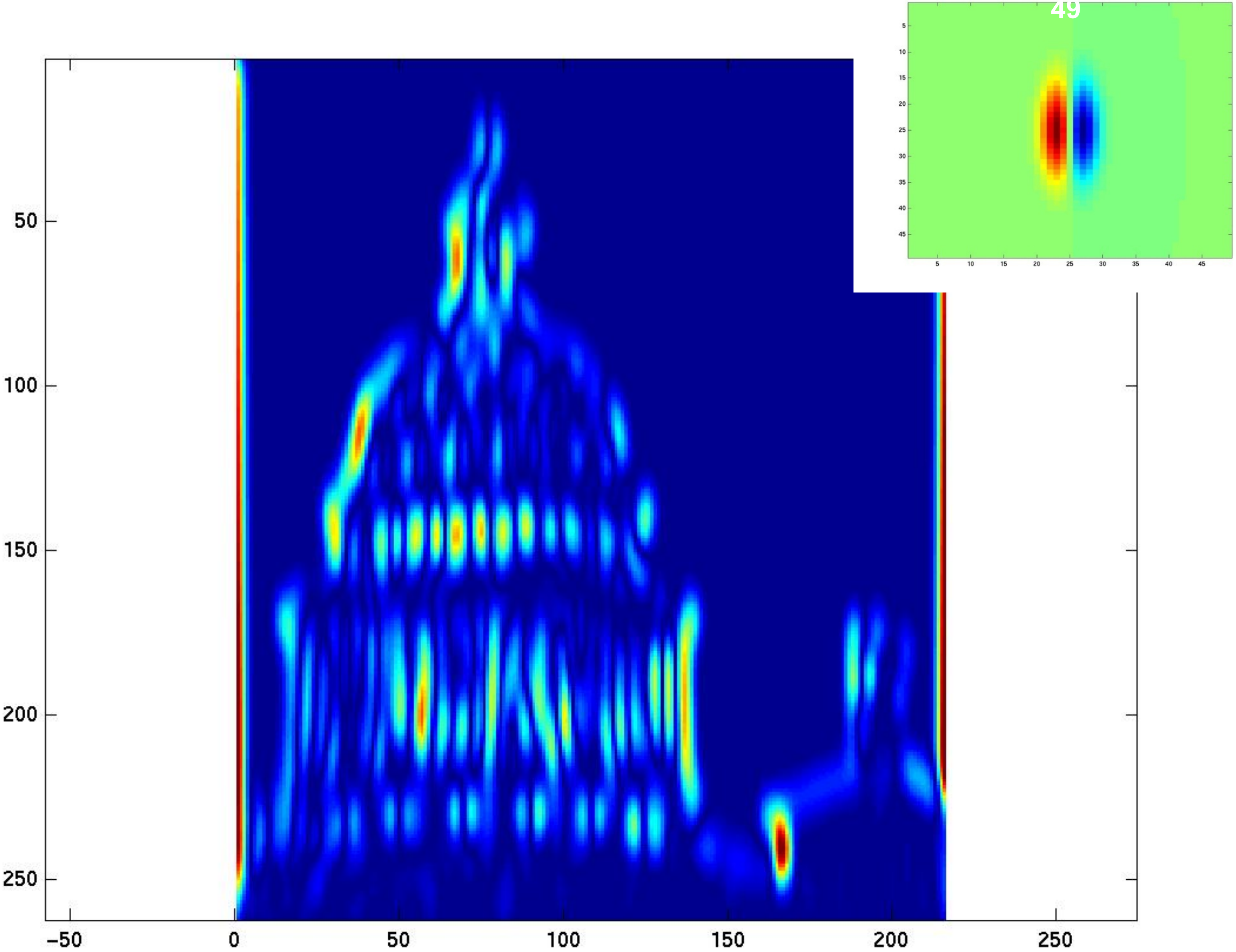
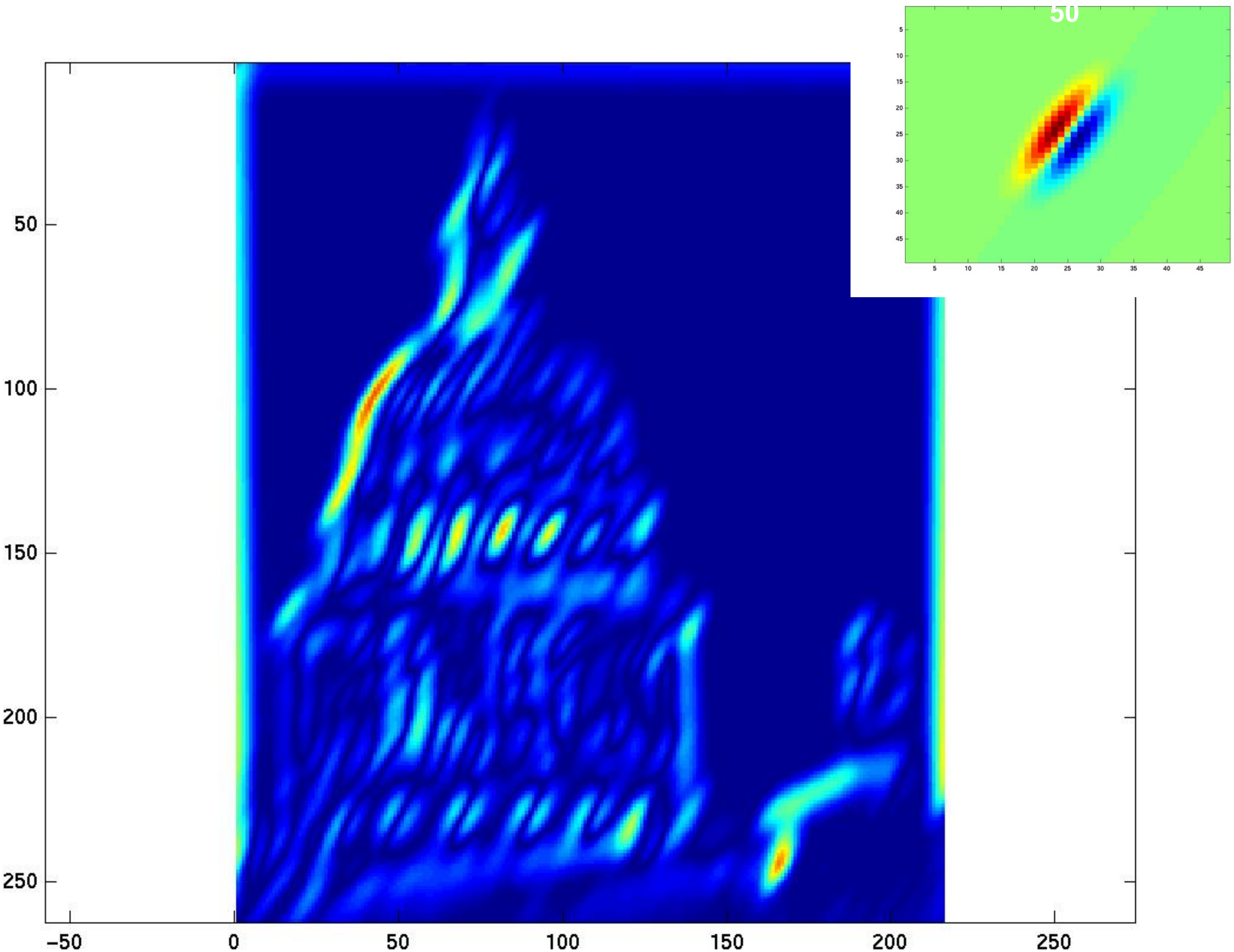
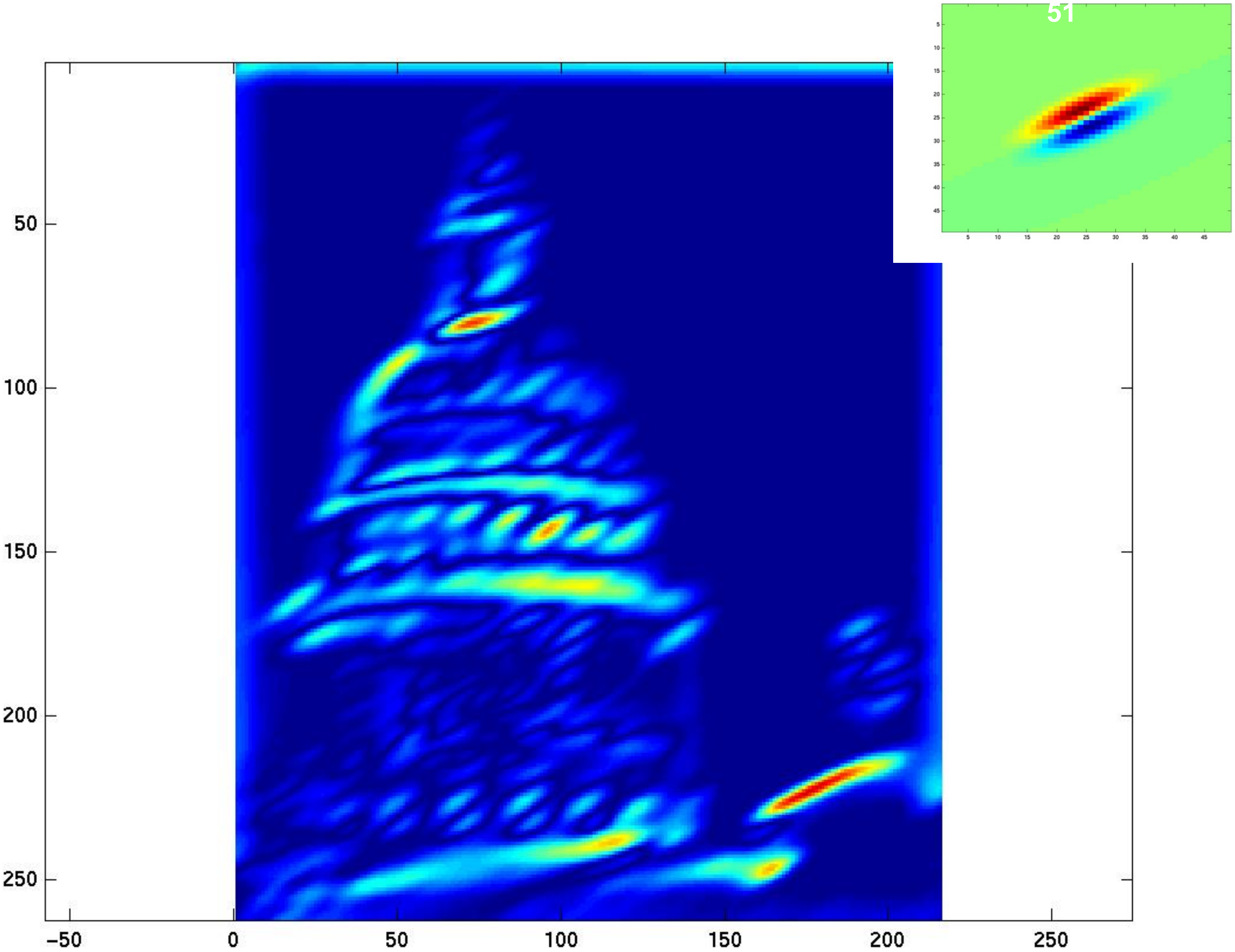
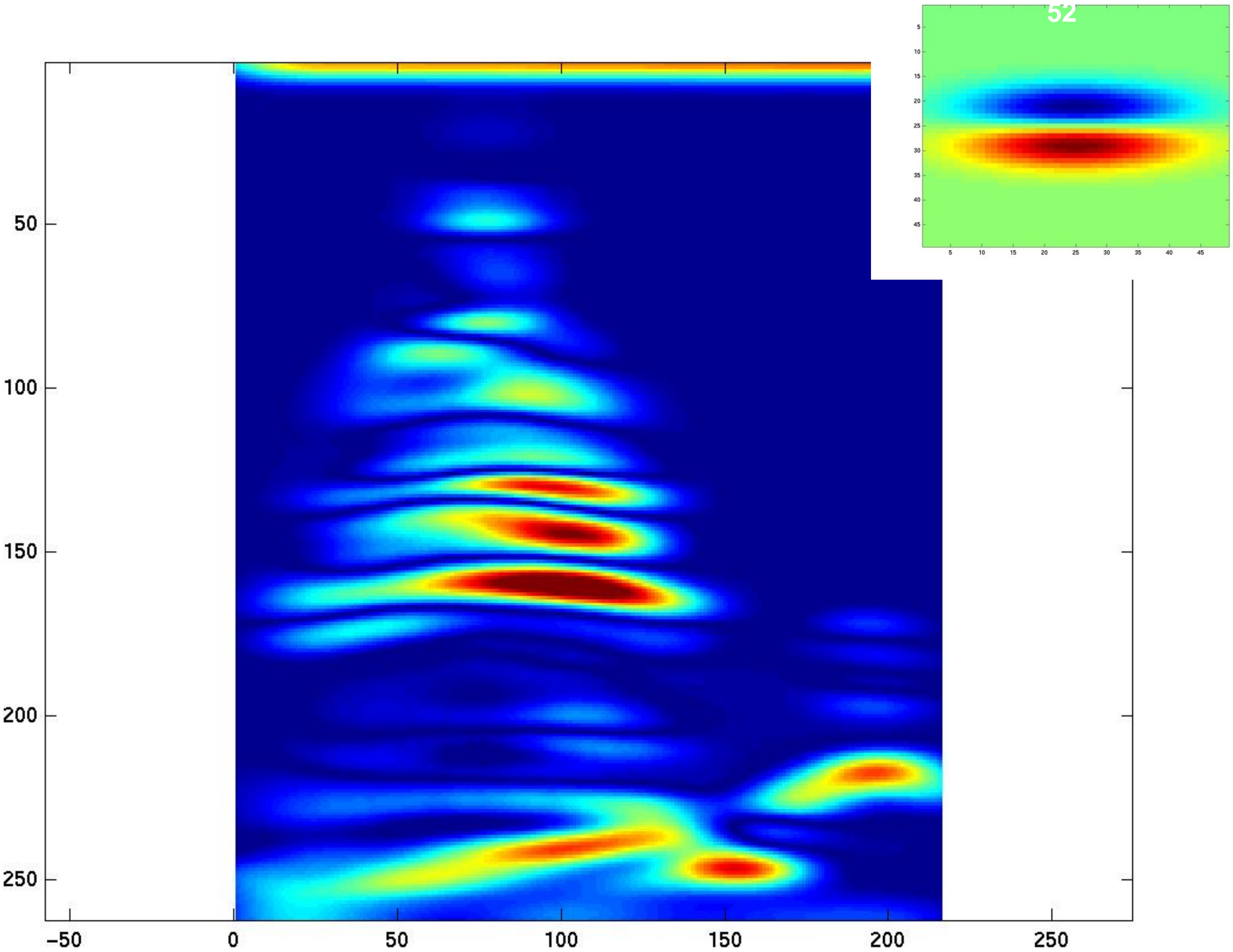

50
100
150
200
250
−50
0
50
100
150
200
250



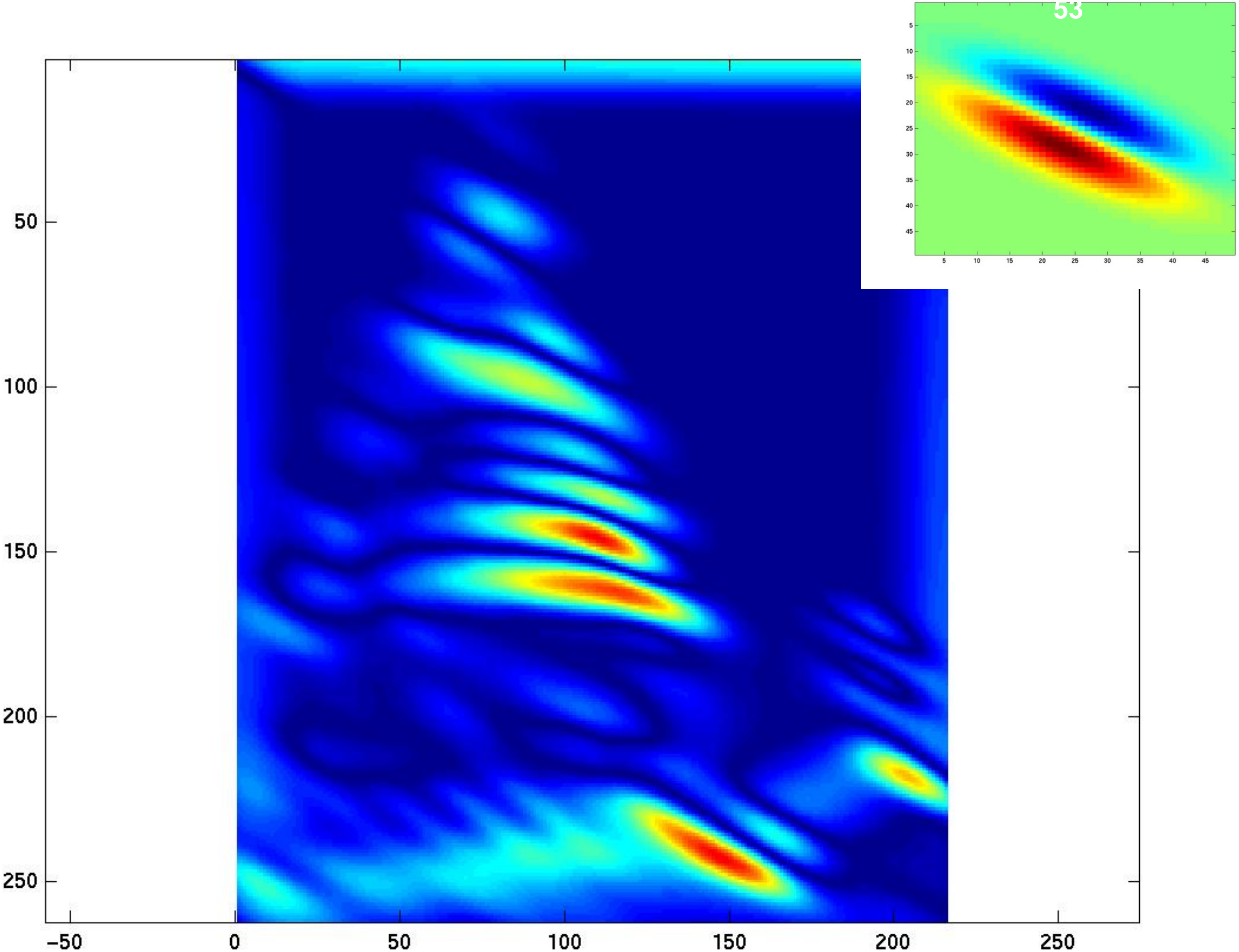
Kristen Grauman



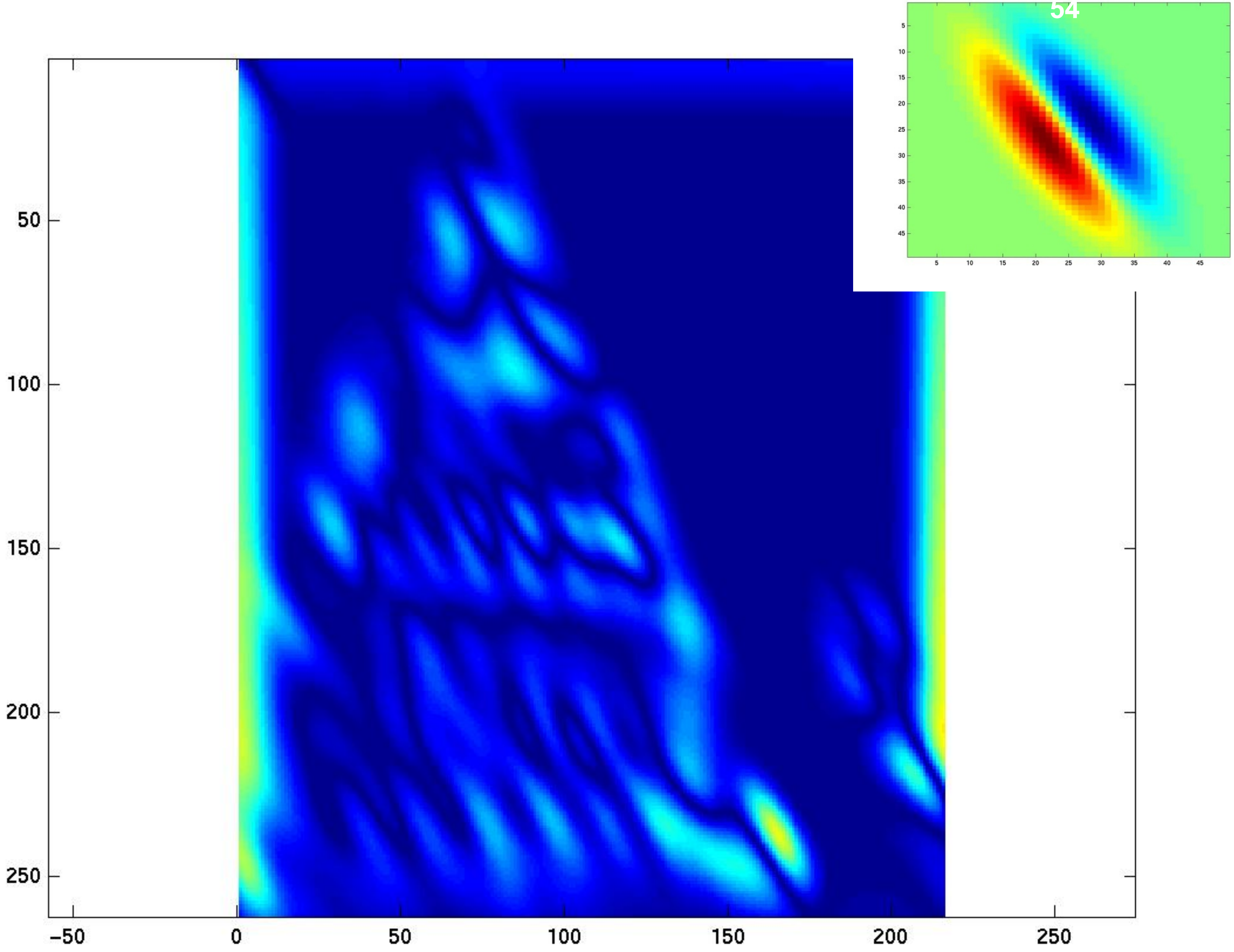
Kristen Grauman



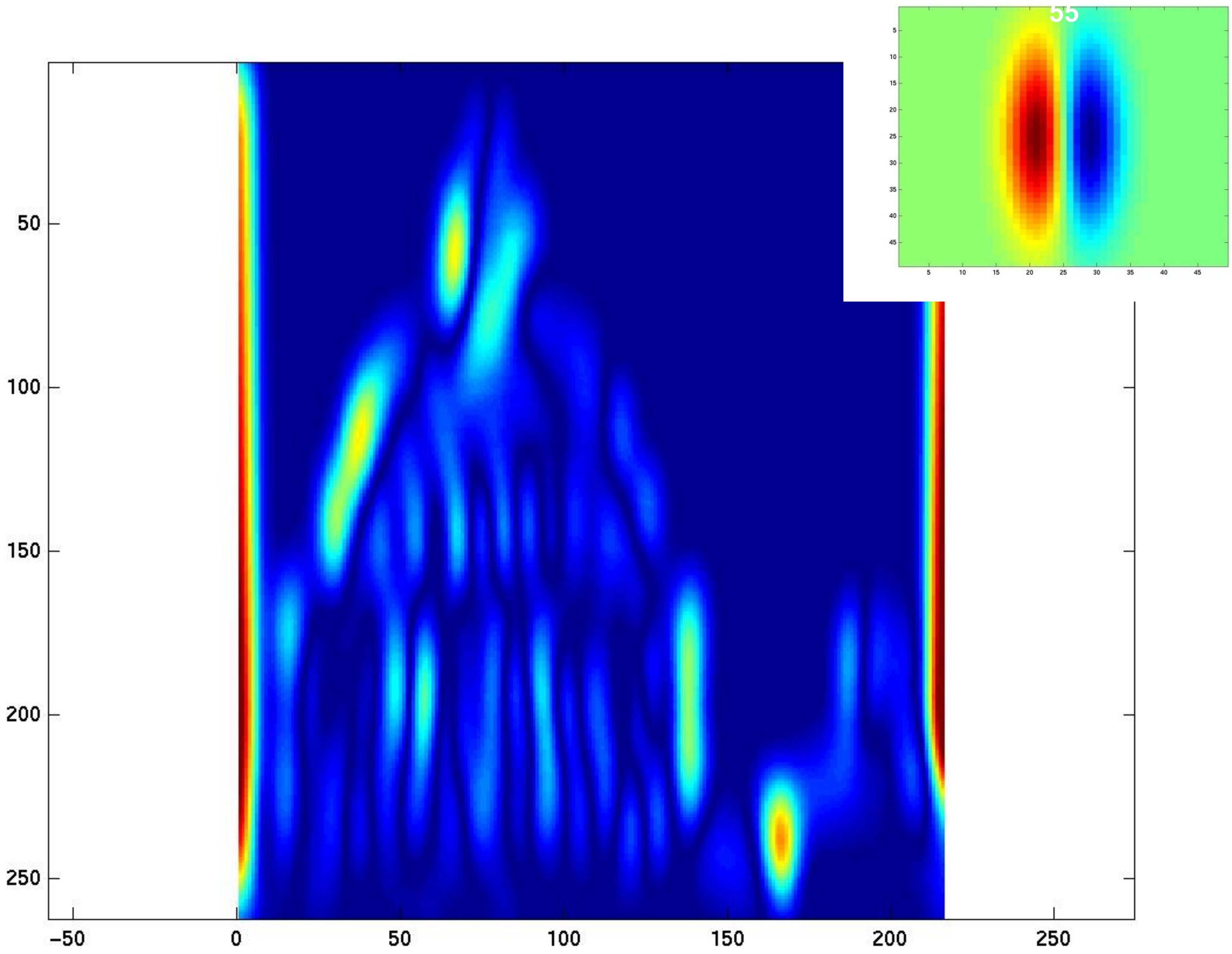
Kristen Grauman



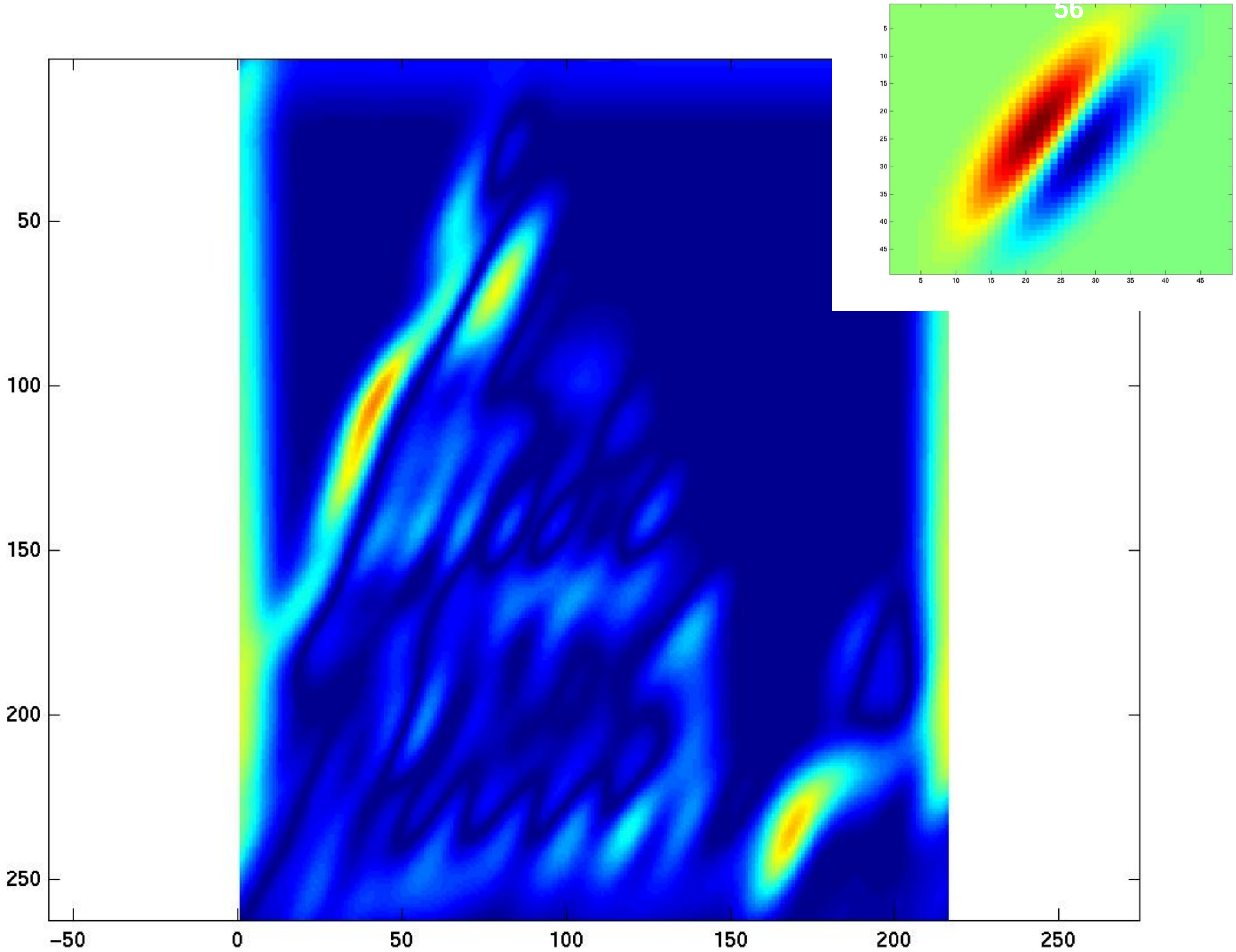
Kristen Grauman



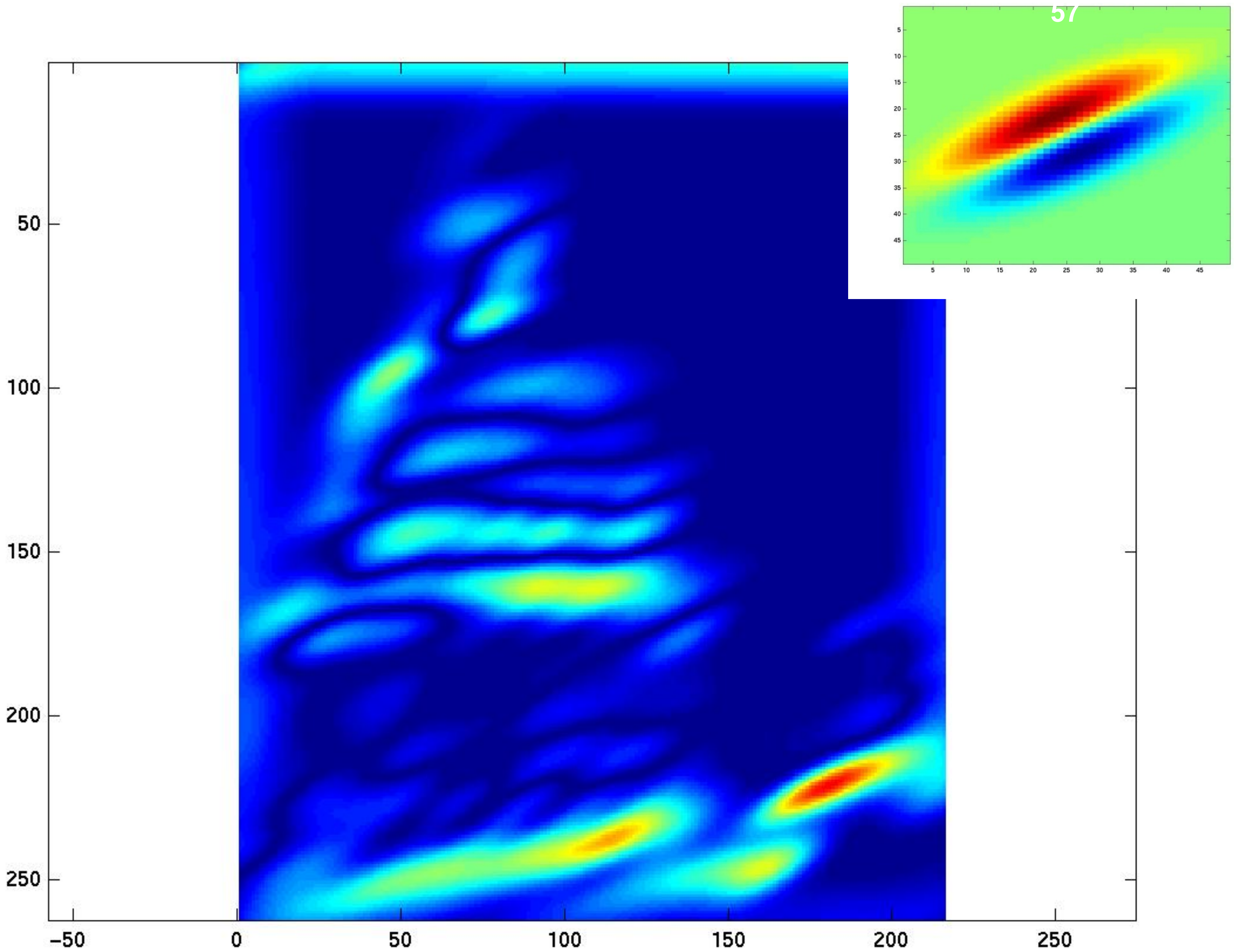
Kristen Grauman

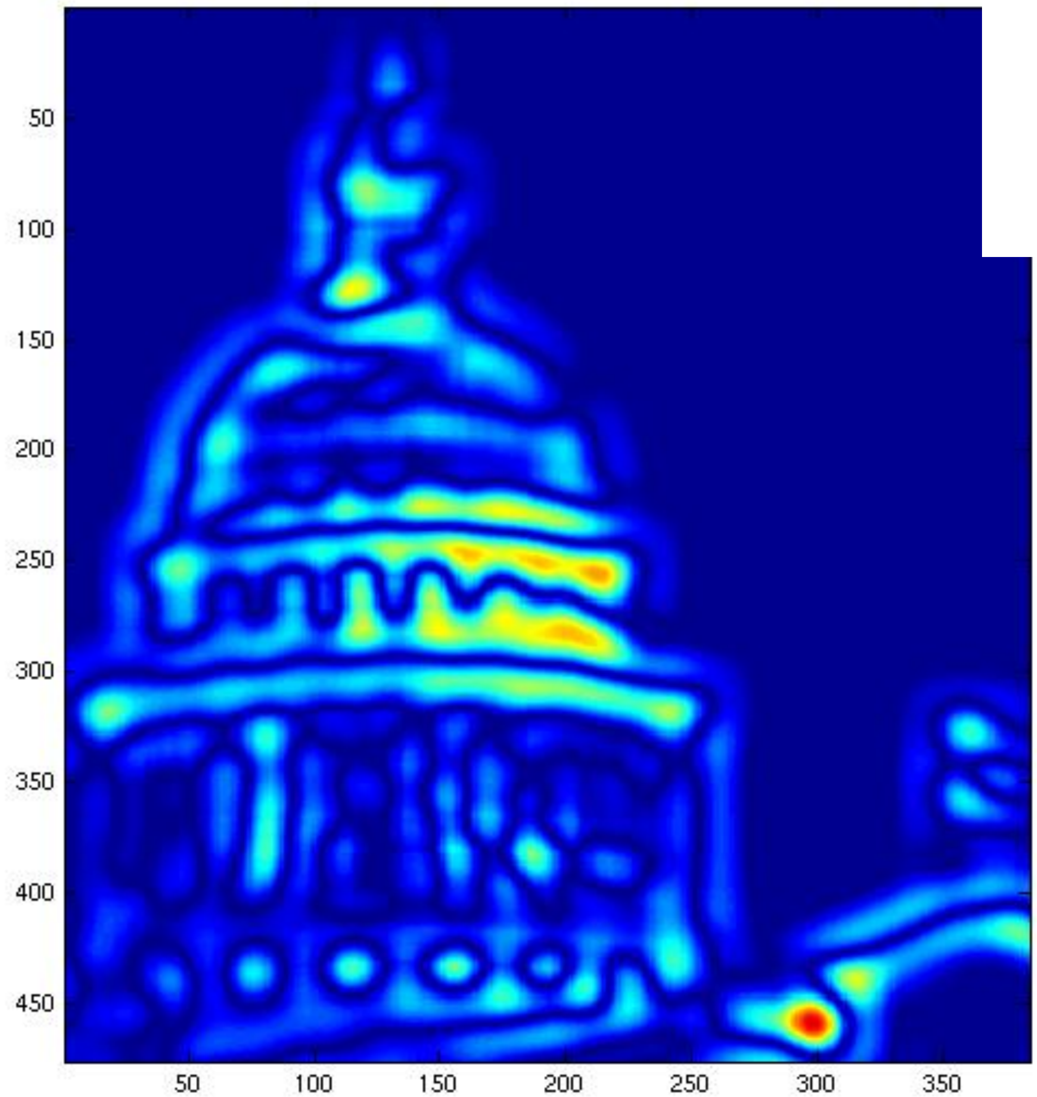


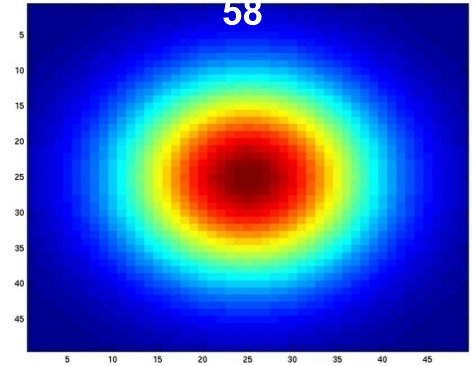
Kristen Grauman



Kristen Grauman

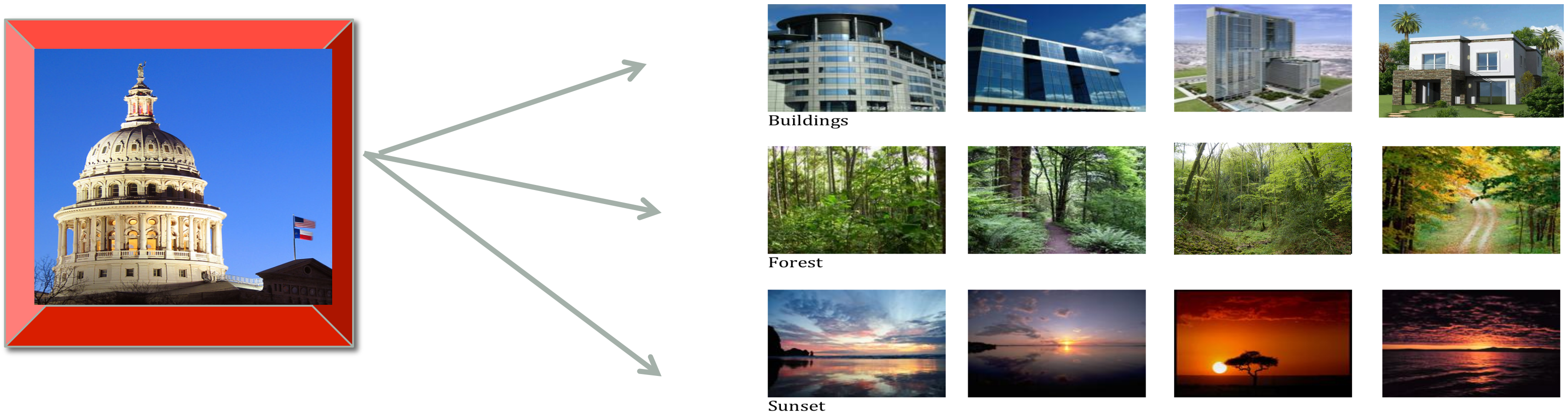

50
100
150
200
250
−50
0
50
100
150
200
250



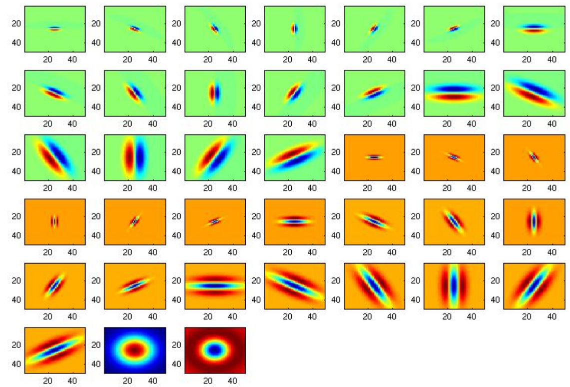


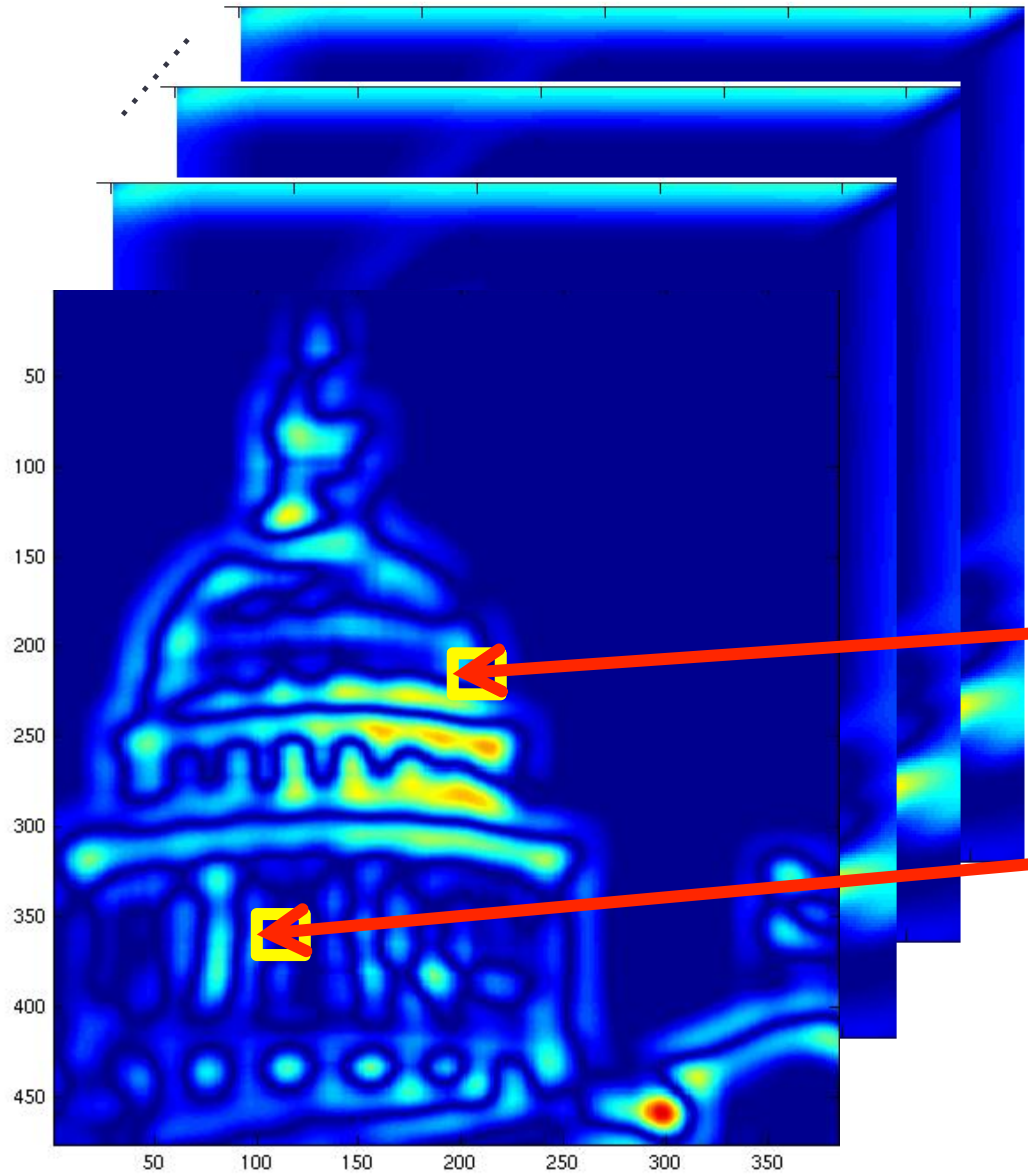
Kristen Grauman

How to recover the image with the most similar texture?



Kristen Grauman





We can form a feature vector from the list of responses at each pixel.

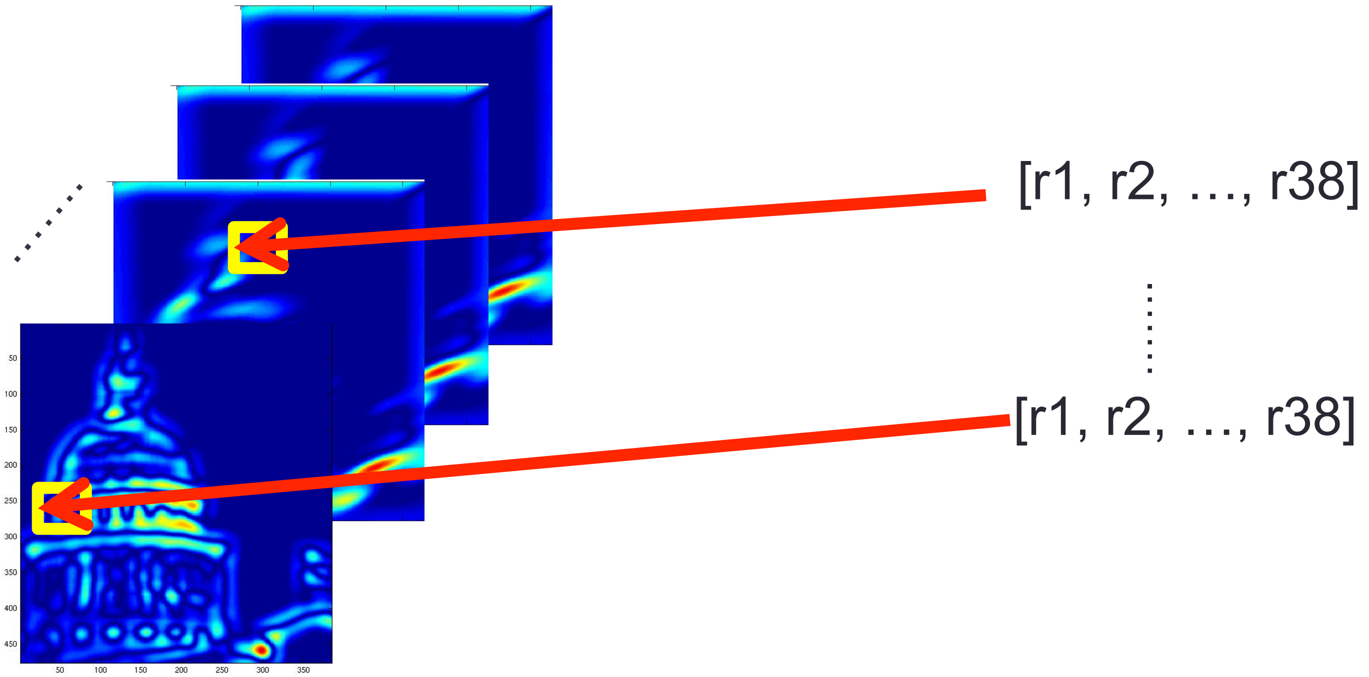
[r1, r2, …, r38]

⋮

[r1, r2, …, r38]

Kristen Grauman

How to go from pixel representation to image representation?



A simple way to represent the whole image is to get the mean abs value of each feature:

$$I \rightarrow f(I)=[\text{mean}_{\text{all pixels}}(|r1|),\ \text{mean}_{\text{all pixels}}(|r2|),\ \ldots,\ \text{mean}_{\text{all pixels}}(|r38|)]$$

How to recover the image with the most similar texture?

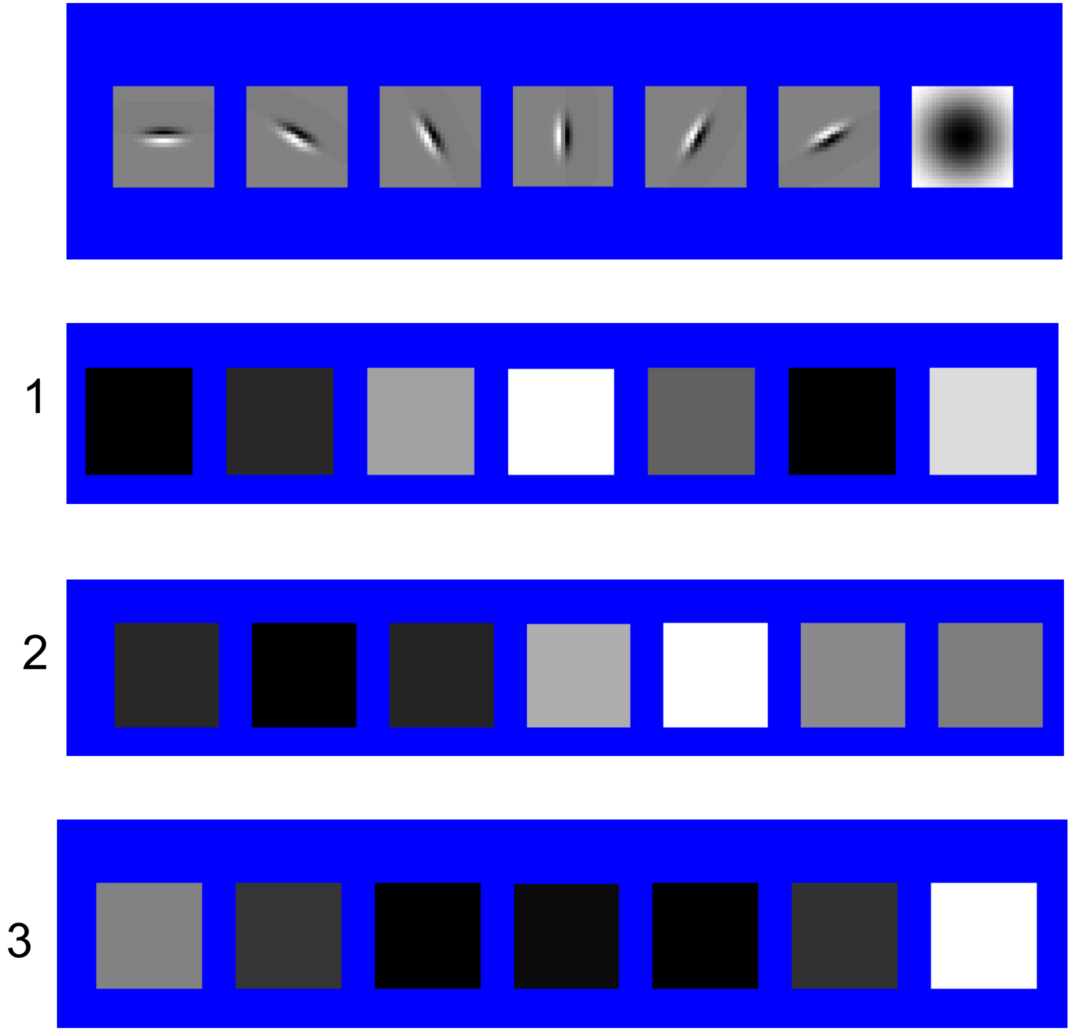
We are looking for the minimal Euclidean distance (L_2) between the feature vectors (f(I)) of the query image and the database images

$$D(f(I_1), f(I_2)) = \sqrt{\sum_{i=1}^{d} (f_i(I_1) - f_i(I_2))^2}$$

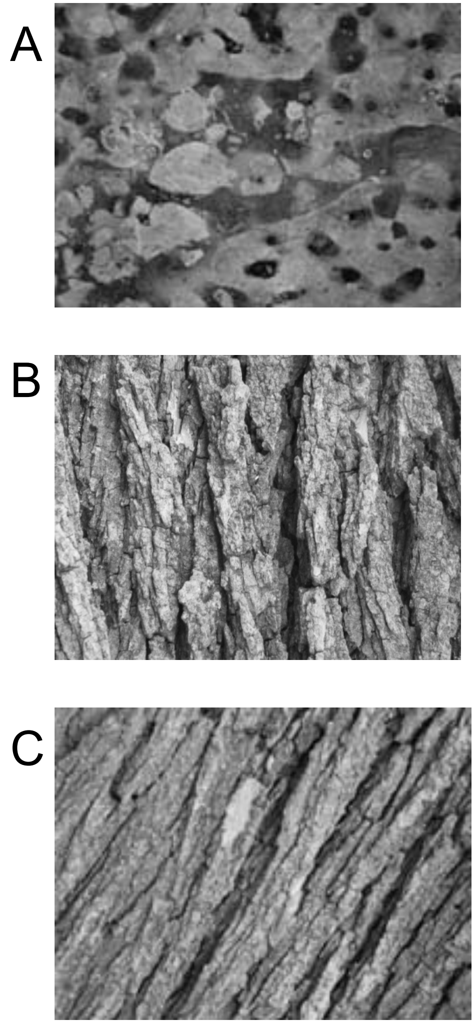
Kristen Grauman

Exercise: Can you match the texture to the response?

Filters



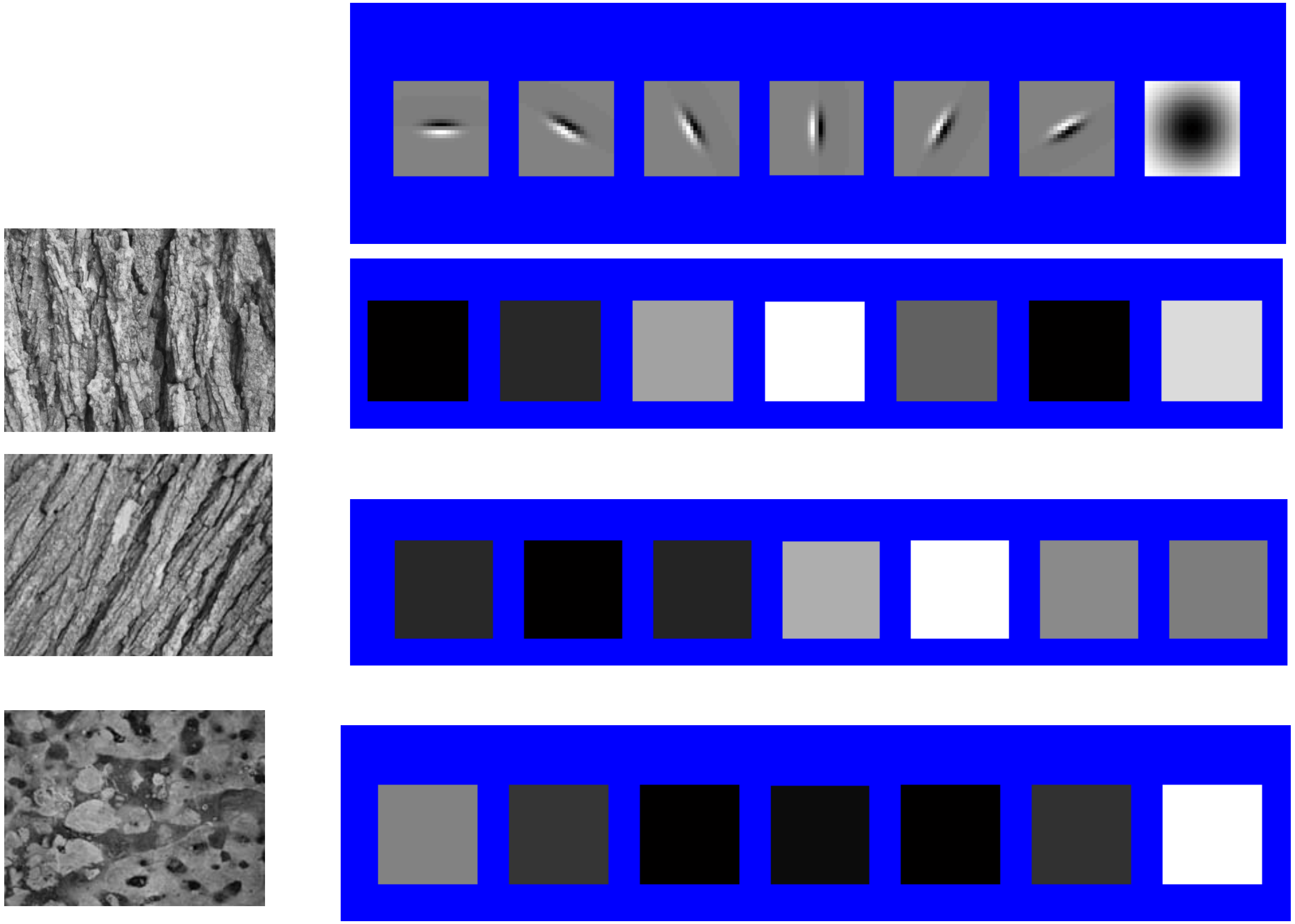
Mean abs responses



Derek Hoiem

Exercise: Representing texture by mean abs response

Filters



Mean abs responses

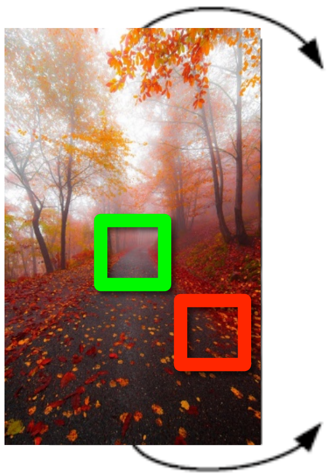
Is the Gaussian filter-based texture recognition contrast invariant?

Derek Hoiem

What is the alternative to recognition of textures?

Recognition of Local Binary Patterns textures - Local Binary Patterns (LBP)

What will happen with the filter convolutions if we change the image contrast?



75	*77*	*77*
48	*56*	*65*
21	*22*	*26*

95	97	97
40	54	72
15	17	20

94	*90*	*52*
96	*92*	*48*
97	*92*	*45*

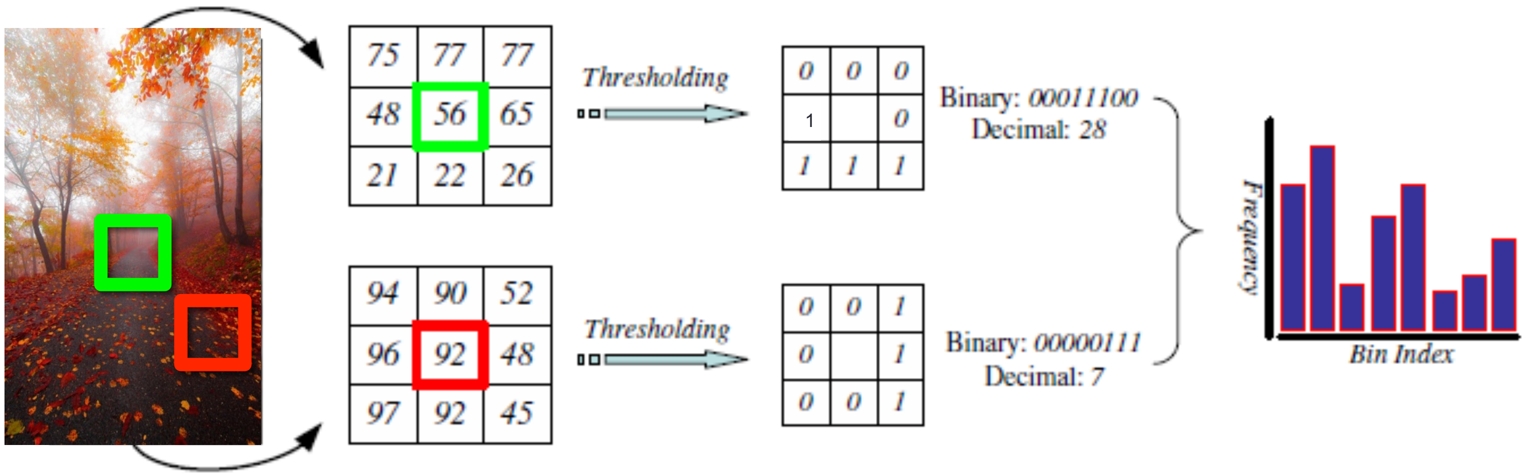
99	93	56
103	96	50
105	96	49

What is not changed?

Recognition of Local Binary Patterns textures (LBP)

Df: The **LBP operator** assigns a label to each pixel of an image by comparing (for example, is it larger than the neighbor?) each neighbor with the value of the central pixel.

The result is considered as a binary number.

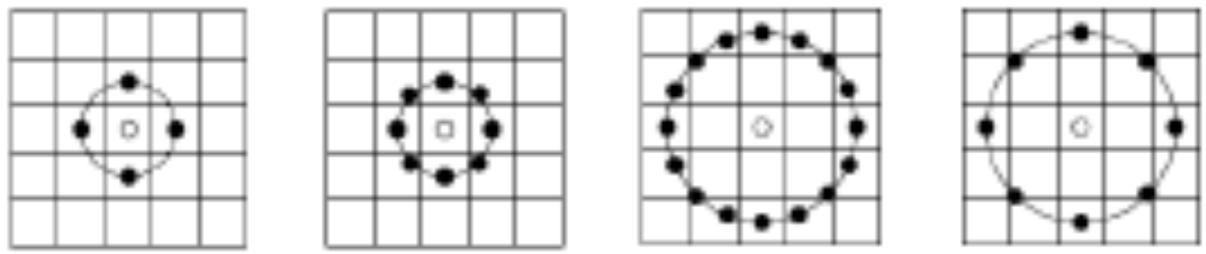


Note: If you use p = 8 neighbors, how many different codes can be generated?

Extension of Local Binary Patterns

To deal with textures at different scales, LBP operator can be extended to use neighborhoods of different sizes.

- Circular neighborhoods and bilinear interpolation of pixel values -> any radius and number of samples of the neighborhood.



(4,1) (8,1) (16,2) (8,2)

Note: If you use p = 16 neighbors, how many different codes can be generated?

Do we need so much different codes?

Uniform LBP

Df: A **LBP is called uniform** iff there are at most two transitions on the binary loop function.

Circular Binary Pattern	# of bitwise transitions	Uniform pattern?
11111111	0	Yes
00001111	1	Yes
01110000	2	Yes
11001110	3	No
11001001	4	No

For example :

00000000 (0 transition), 11100011 (2 transitions) -> uniform
01010000 (4 transitions), 01110101 (6 transitions) -> no uniform

Each uniform pattern -> its proper bin of the histogram.

All transitions are accumulated in a non-uniform bin (eg bin 0).

Uniform LBP

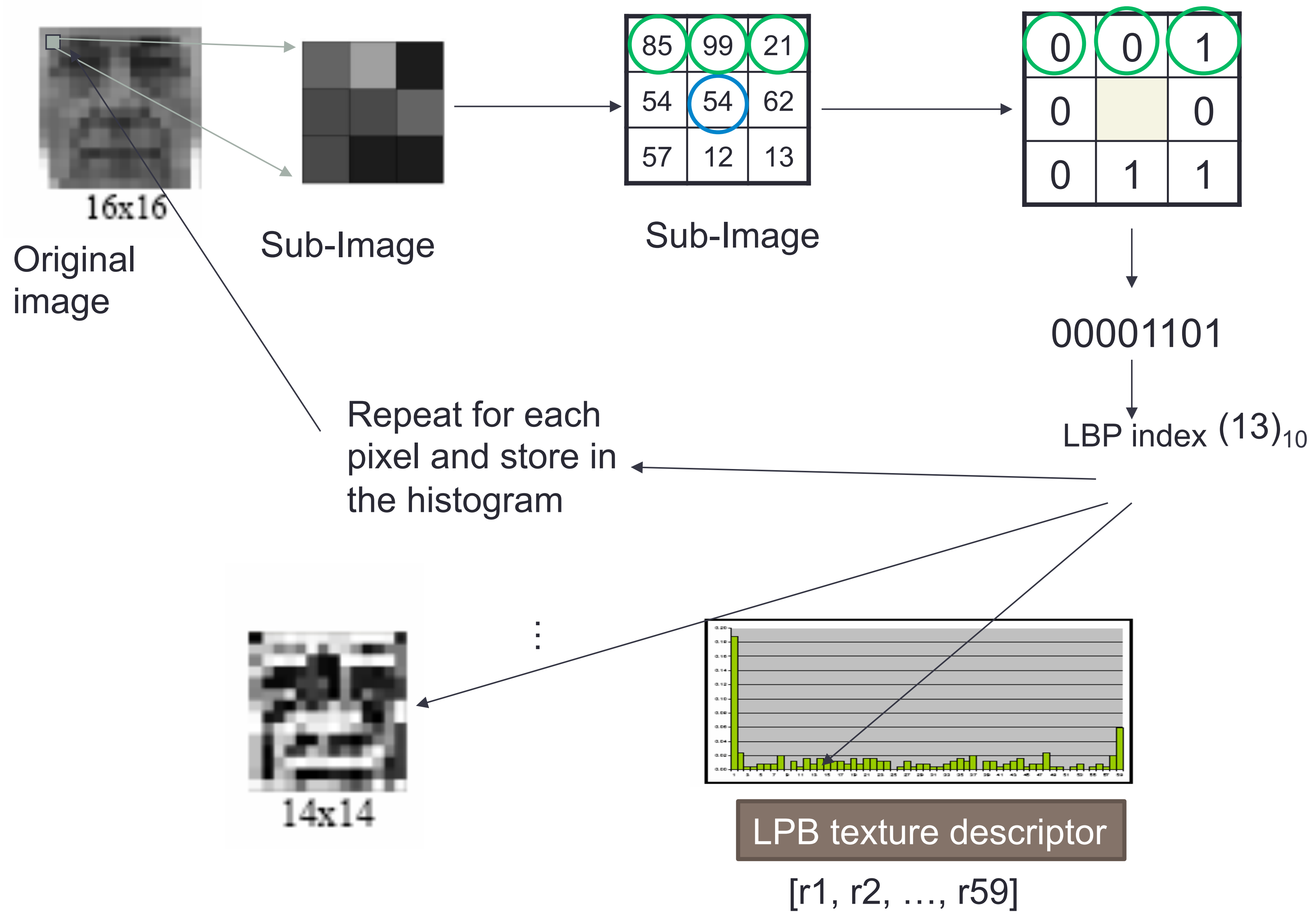
Considering P = 8, we get eight patterns (bits), all possible values are 256 (i.e. 2^8), but only 58 are uniform.

We construct a histogram for the 58 bins + one bin accumulating all non-uniform patterns.

A histogram of 59 bins represents 76.95% of the reduction of the image feature vector (256 bins histogram).

Uniform Label (decimal)	Uniform Label (binary)	Number of Transitions	$LBP^{u2}_{(8,R)}$ histogram bin
non uniform patterns	non uniform patterns	>2	0
0	00000000	0	1
1	00000001	1	2
2	00000010	2	3
3	00000011	1	4
4	00000100	2	5
⋮	⋮	⋮	⋮
251	11111011	2	54
252	11111100	1	55
253	11111101	2	56
254	11111110	1	57
255	11111111	0	58

Uniform LBP- Algorithm



Properties of LBP vs. Gaussian filters

Pros
- Simple theory
- Computational simplicity
- Fast
- Compact
- Invariant to image illumination changes

Cons
- Can be too simple sometimes
- Which neighbours to consider to be decided.

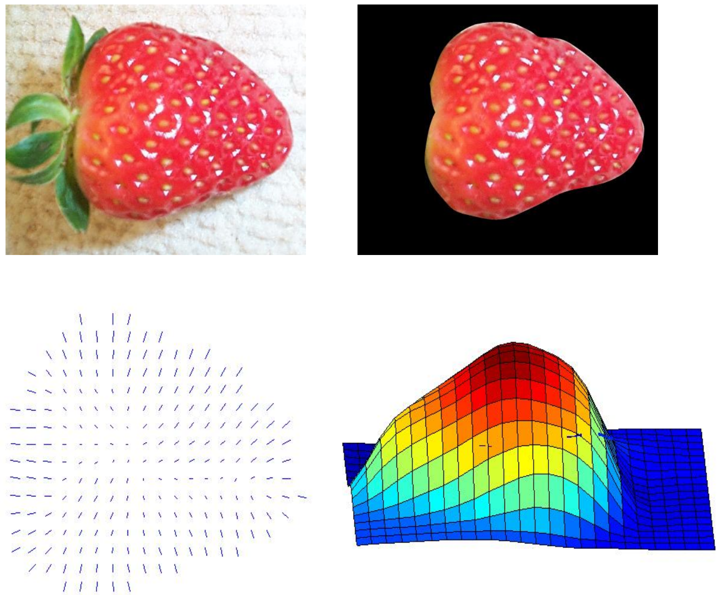
Pros
- Able to capture wide scope of textures
- Computational simplicity
- Compact
- No parameters

Cons
- Non-Invariant to image illumination changes

Example uses of texture in computational vision

Shape from texture

- Use deformation of texture from point to point to estimate surface shape



Pics from A. Loh: http://www.csse.uwa.edu.au/~angie/phdpics1.html

Textures and Orientation

The geometric variations of a surface produce three effects on the elements of texture:

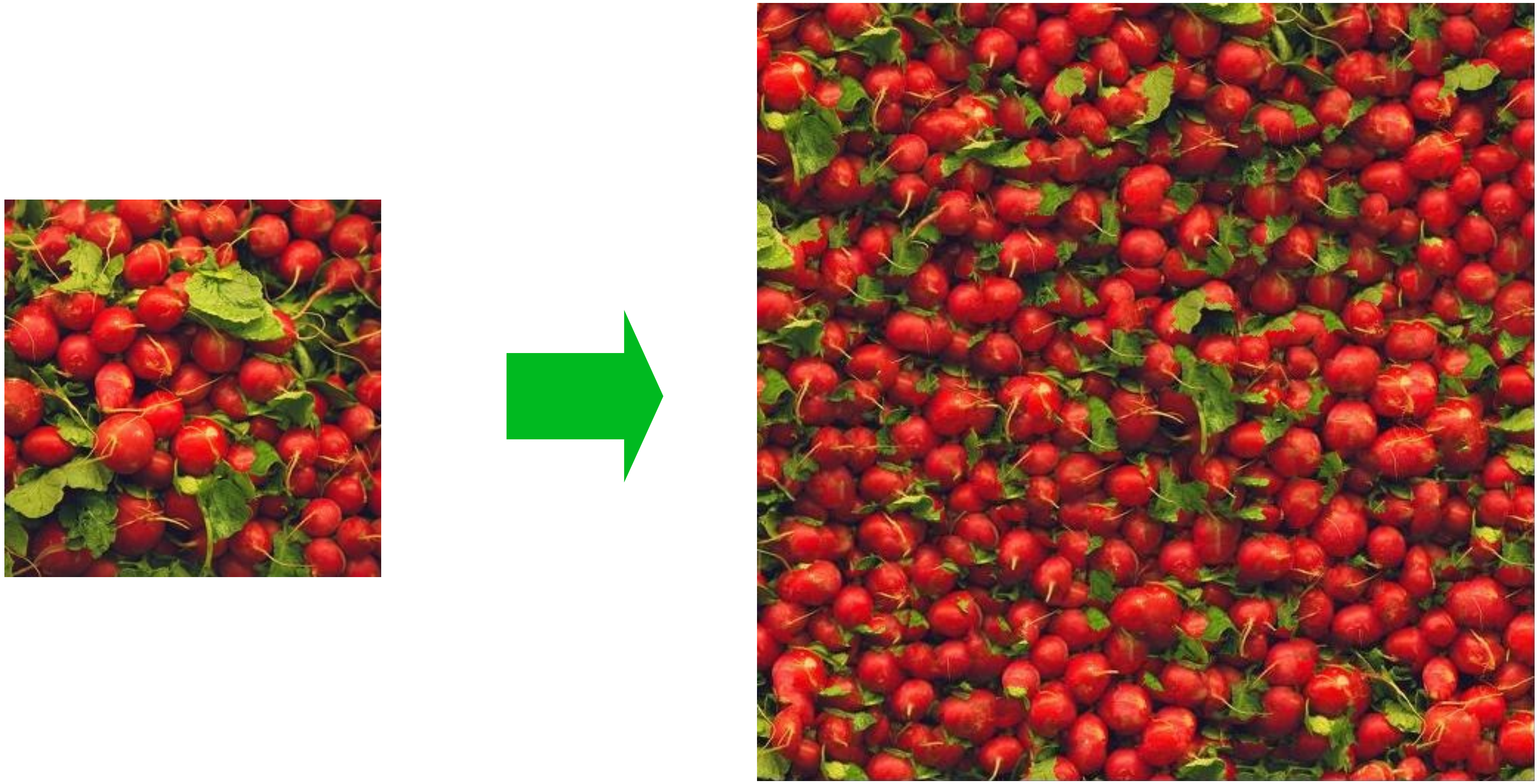
- Change in the density of the elements.
- Foreshortening, or change in size due to perspective.
- Rescaling.

The foreshortening is only caused by the orientation of the surface!!!.

Idea: The foreshortening can be characterized by changes in the local distribution of the contour orientation of the textons.

Texture synthesis

- Goal: create new samples of a given texture
- Many applications: virtual environments, hole-filling, texturing surfaces



Synthesizing textures when constructing 3d models of archaeological sites

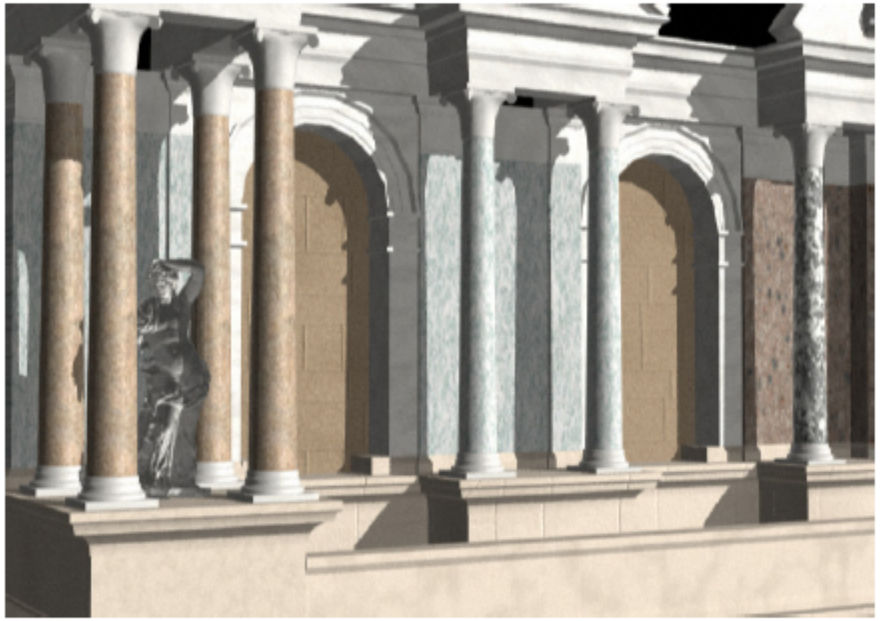


Figure 12. The Nymphaeum at the upper agora of Sagalassos with differently textured pillars. Overview of one half of the building (symmetric)

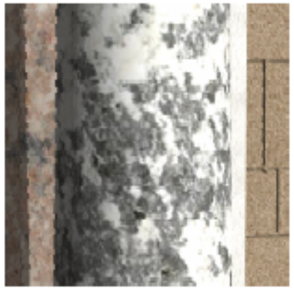
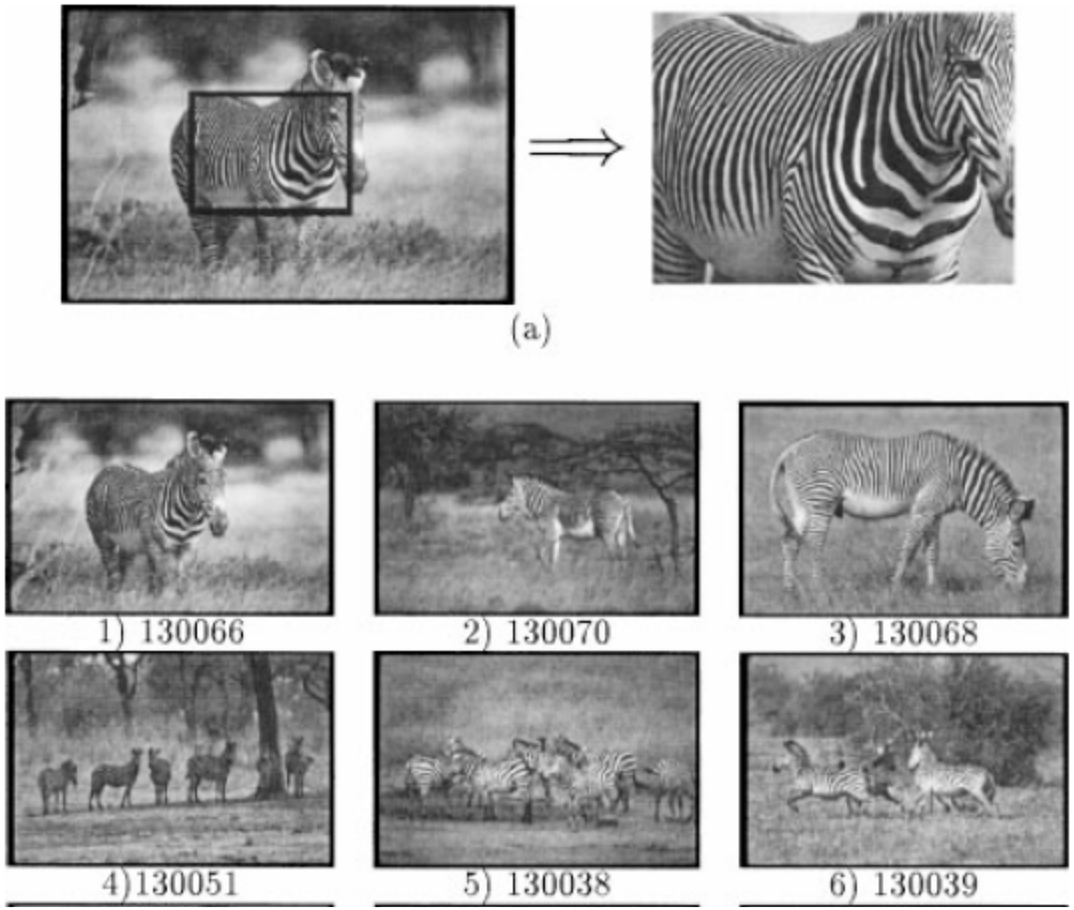


Figure 14. Nymphaeum pillars and back wall fragments in detail

Segmenting aerial imagery by textures

Kristen Grauman

http://www.airventure.org/2004/gallery/images/073104_satellite.jpg



Texture features for image retrieval

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,

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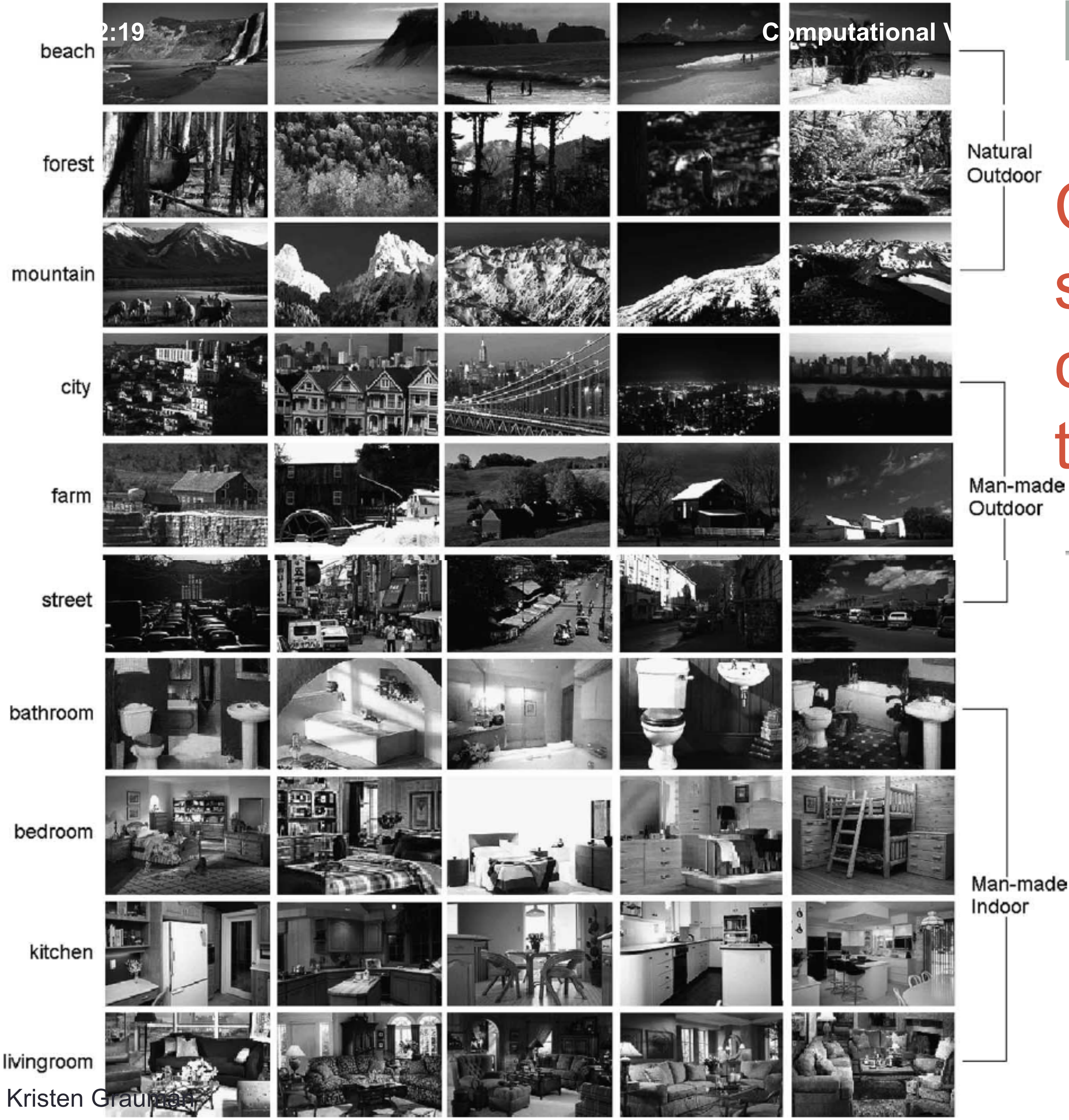
Characterizing scene categories by texture



L. W. Renninger and J. Malik. When is scene identification just texture recognition? Vision Research 44 (2004) 2301–2311

Image retrieval


Buildings


Forest


Sunset

Let us consider an image database of different views: buildings, forest, sunset, etc.

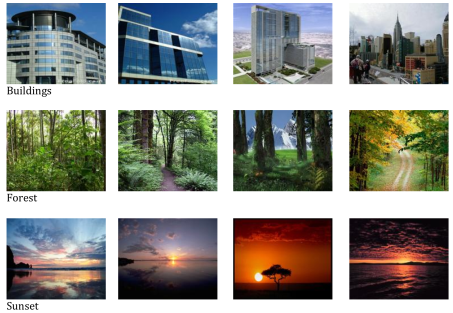
Given a query image, we want to recover the k most similar images.

Image retrieval

First of all we need to define the feature space:

- Texture?
- Color?
- Texture+color?

Let us define our feature descriptors composed by the LBP descriptors.



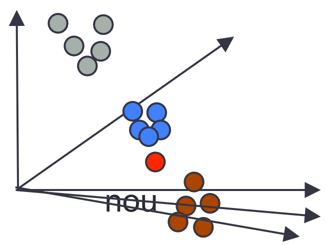
1,2,5,4,7...
4,2,4,2,1...
...
2,2,1,1,1...
3,1,1,2,3...
......
3,4,5,6,1...
4,4,3,4,4...

4,2,3,4,4...

Image retrieval

We need a method to recover the k nearest examples, according to their descriptors.

- We can use the method K Nearest Neighbors (k-nn).



KNN method: gets the K nearest neighbors and determines which class they belong mostly.

Matlab:

Knnsearch: Find K nearest neighbors.

IDX = knnsearch(X,Y) finds the nearest neighbor in X for each point in Y. X is an MX-by-N matrix and Y is an MY-by-N matrix. Rows of X and Y correspond to observations and columns correspond to variables. IDX is a column vector with MY rows. Each row in IDX contains the index of the nearest neighbor in X for the corresponding row in Y.

Retrieval using LBP textures

11000011
11101111
11110000

Image LBP histogram

11000011
11101111
11110000

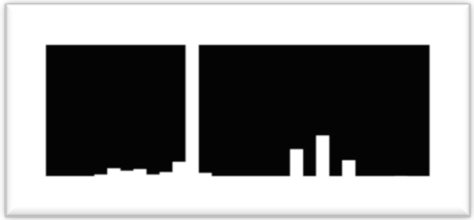
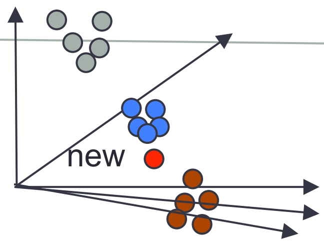


Image LBP histogram



Knn will return the k most similar pictures.

Classifying materials, "stuff"

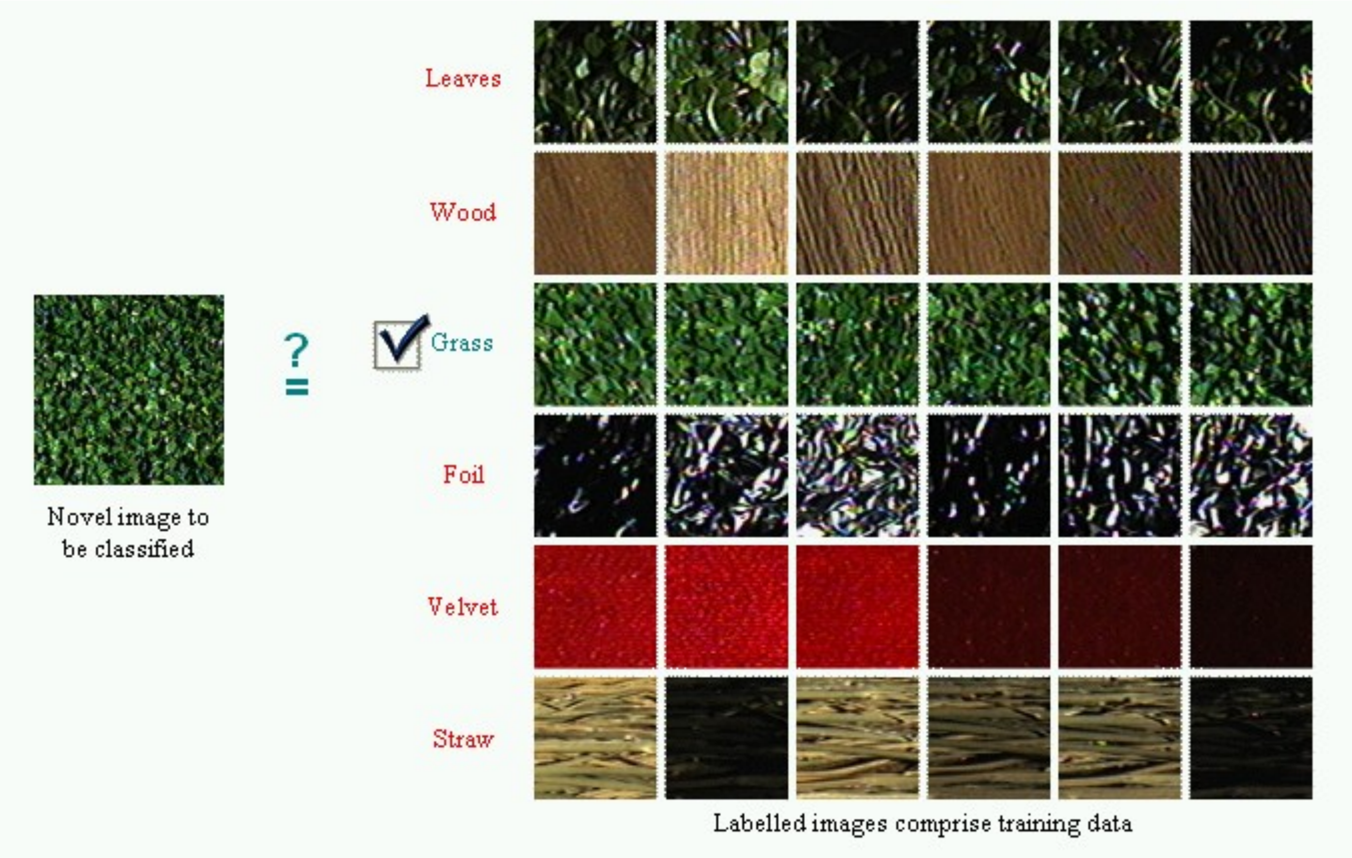


Figure by Varma & Zisserman

Knn will return the k most similar pictures.

Assign the class with the majority label.

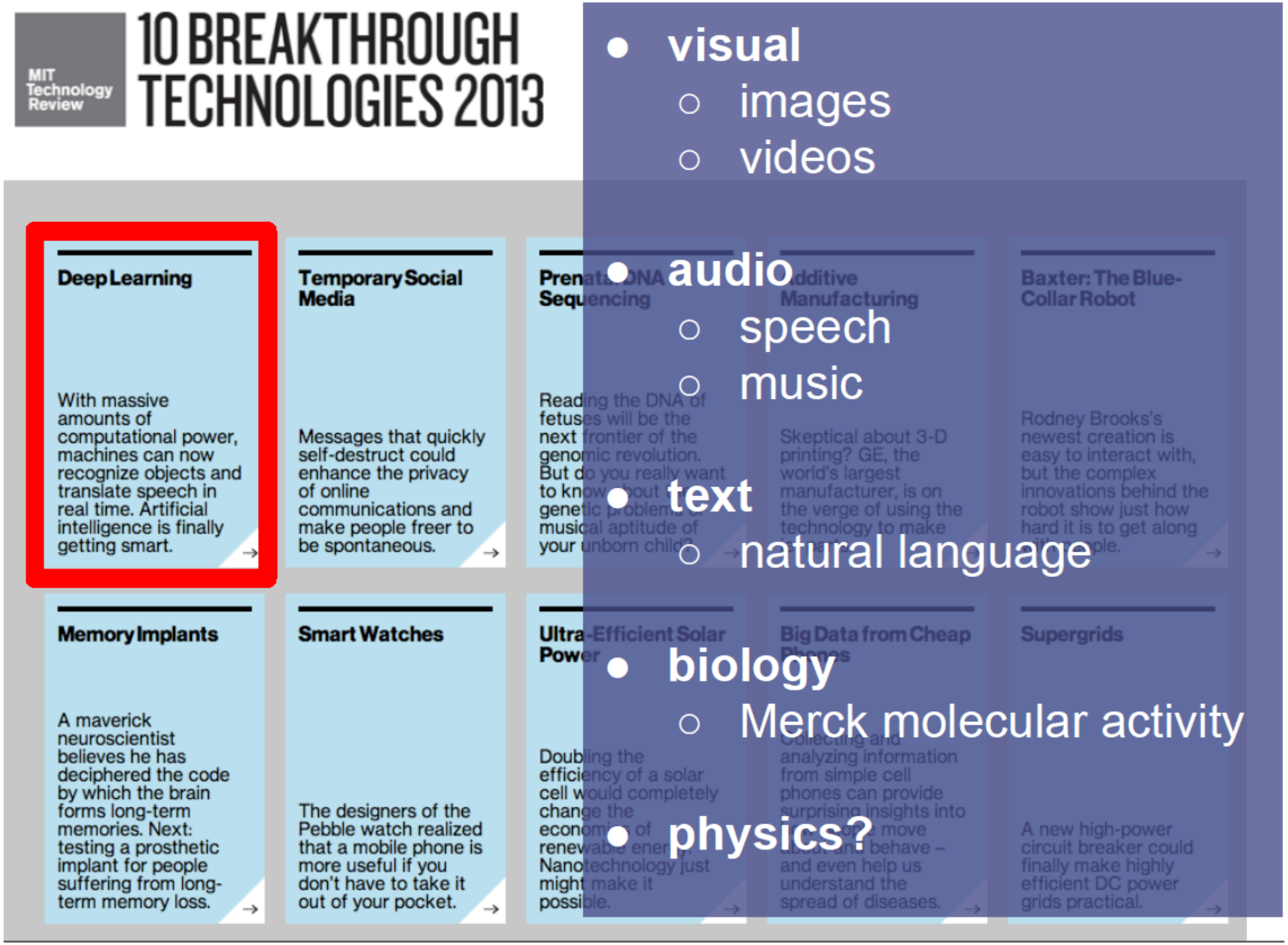
Kristen Grauman

Questions

- Can we substitute the texture descriptor with the Gaussian filters descriptor?
- Which would be the dimension in this case of the feature space?
- Can we add color features combined with the texture features?
- How to include spatial information in the descriptor? Would it be useful?
- Which method works better? Which is faster?
- What other distances is knn using? Check if the Euclidean is the good enough compared to the rest of distances.
- What does happen with the texture descriptor if there are two regions with very different texture in the image?

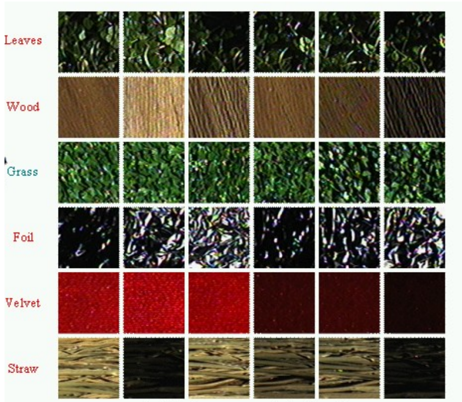
Drawbacks

What are the optimal texture features for image classification?

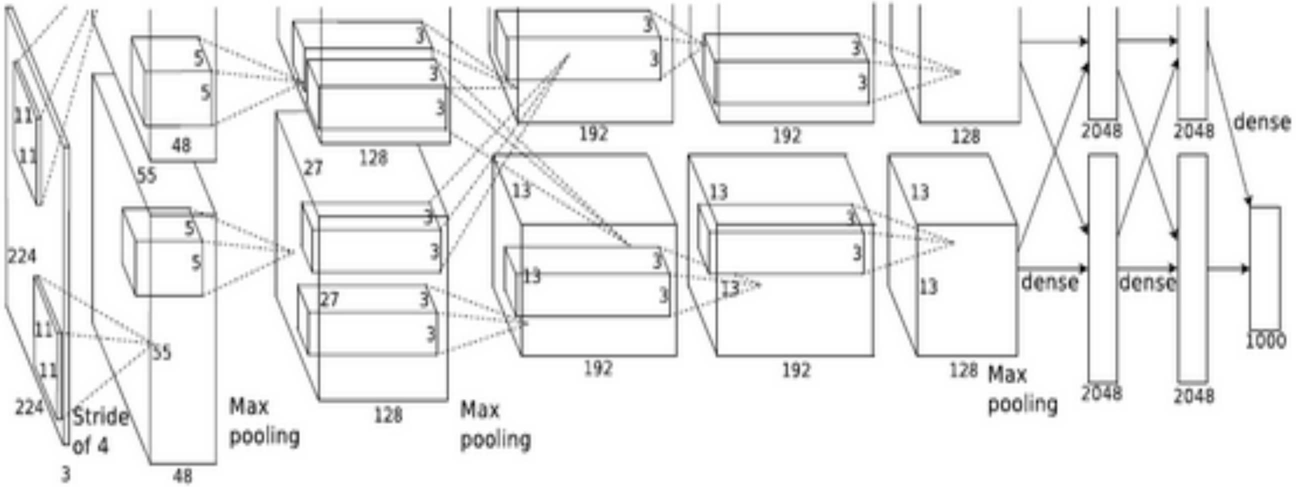


- **visual**
  - images
  - videos
- **audio**
  - speech
  - music
- **text**
  - natural language
- **biology**
  - Merck molecular activity
- **physics?**

How to recognize images (textures)?

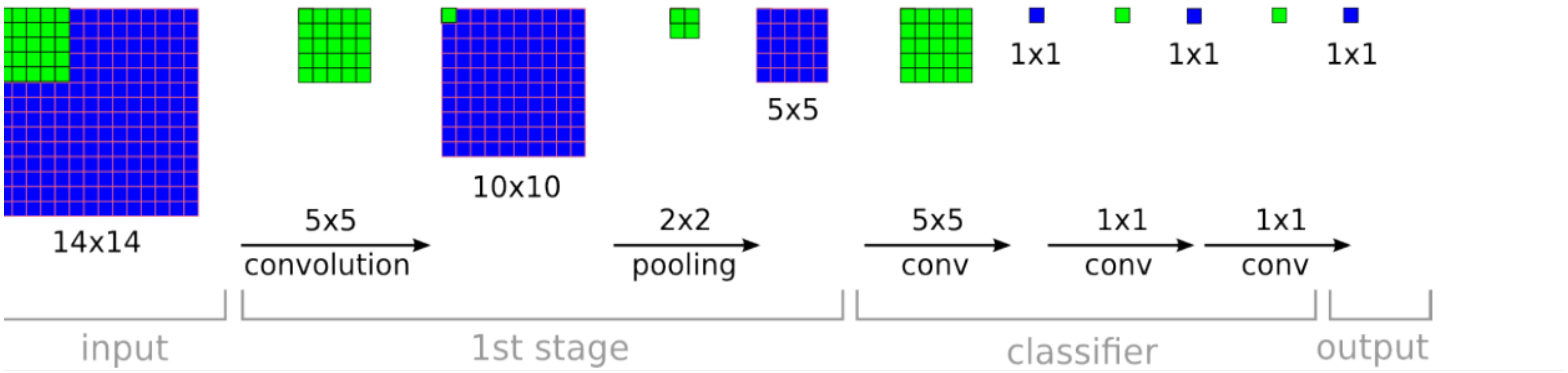


Labelled images comprise training data



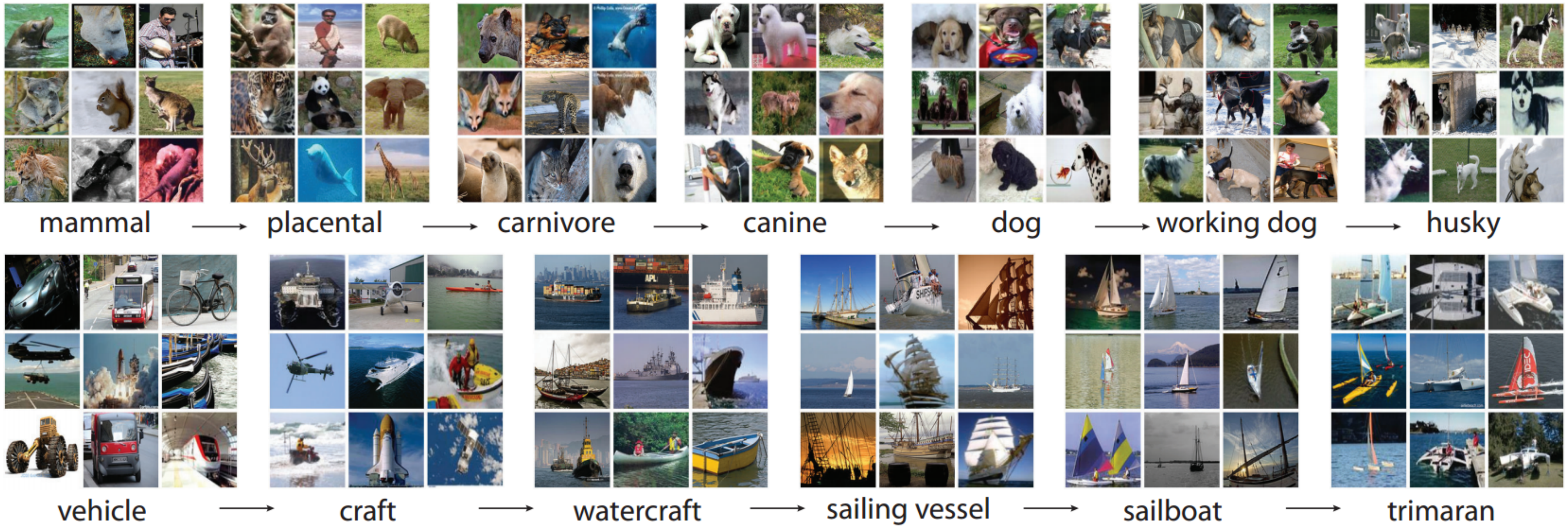
- Convolutional Neural Networks

What is a ConvNet?



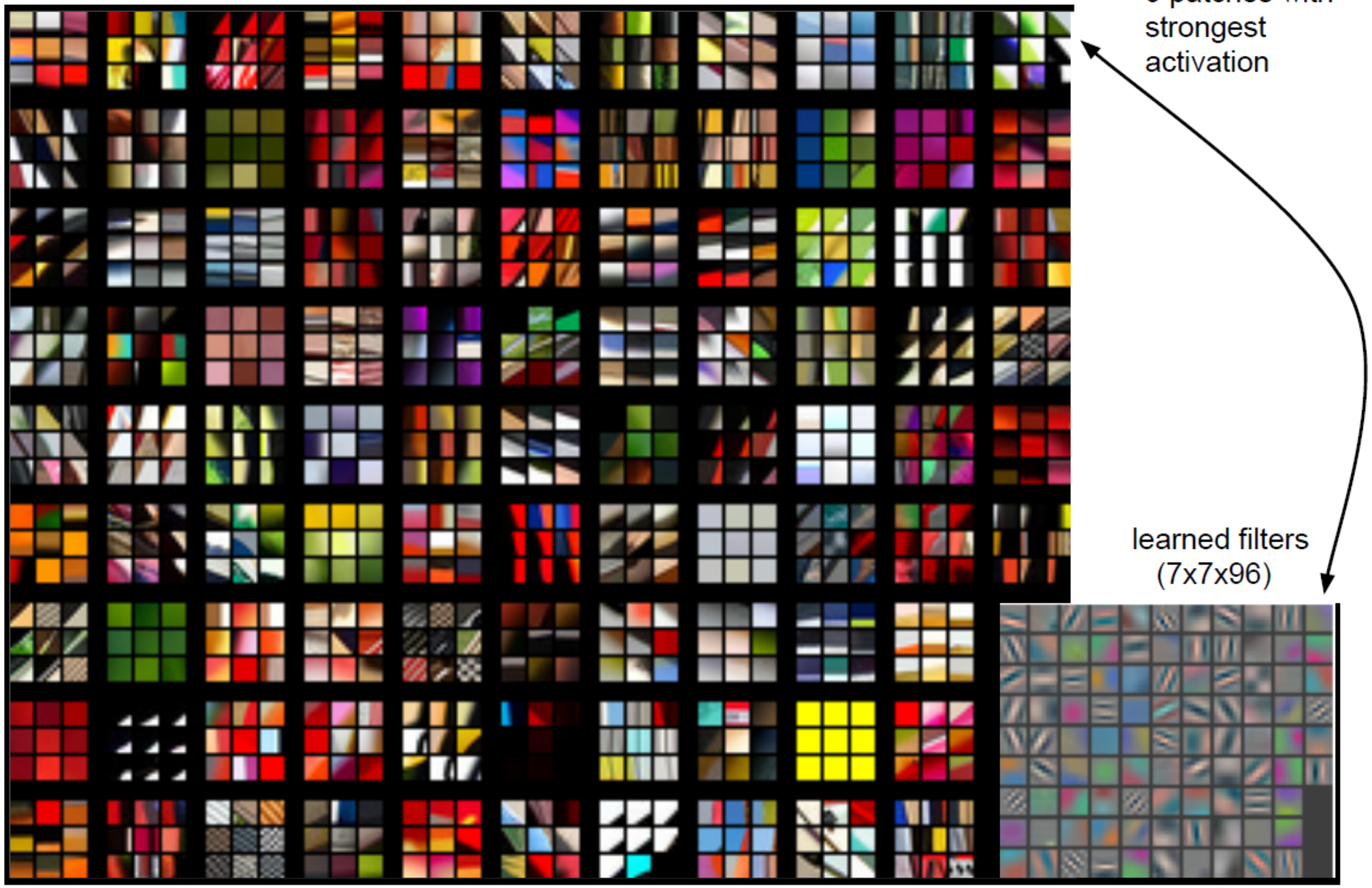
Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS, 2012.

ImageNet



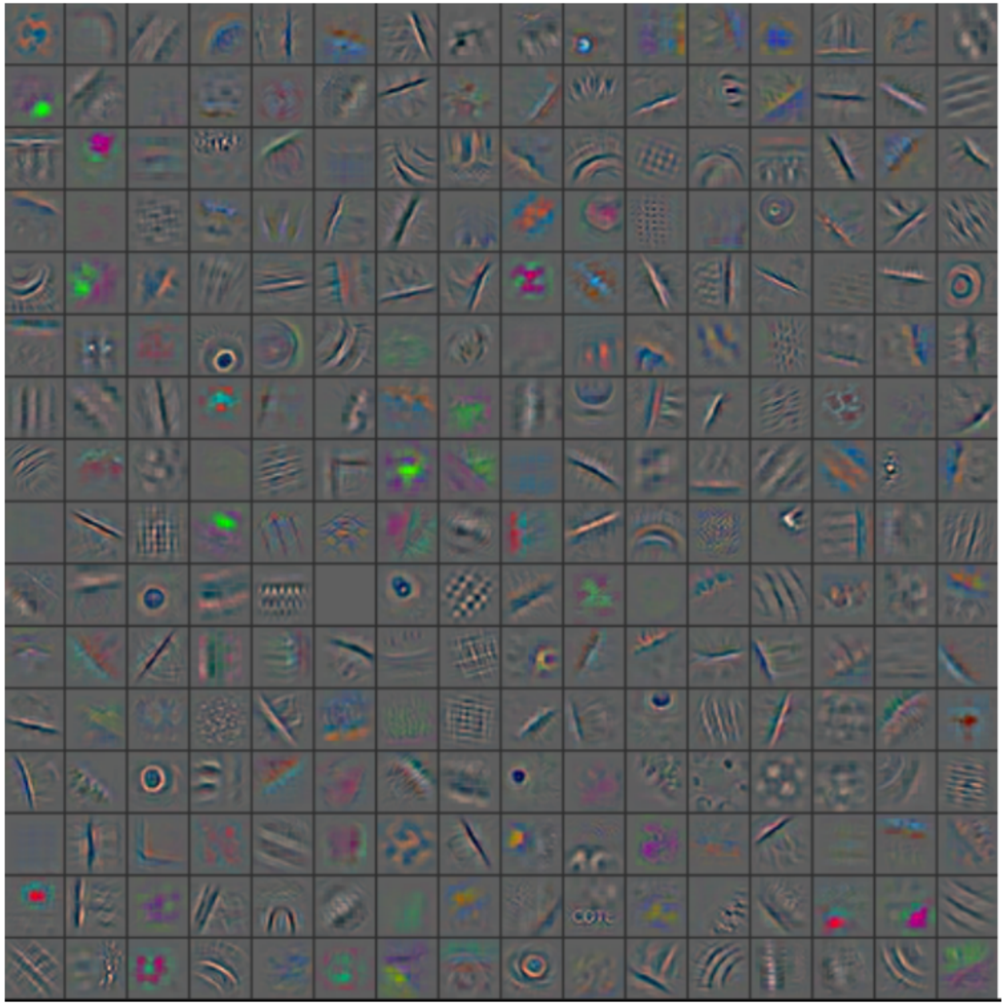
ImageNet: 15 millions of images!!! Used to train the CNN.

Learned convolutional filters: Stage 1



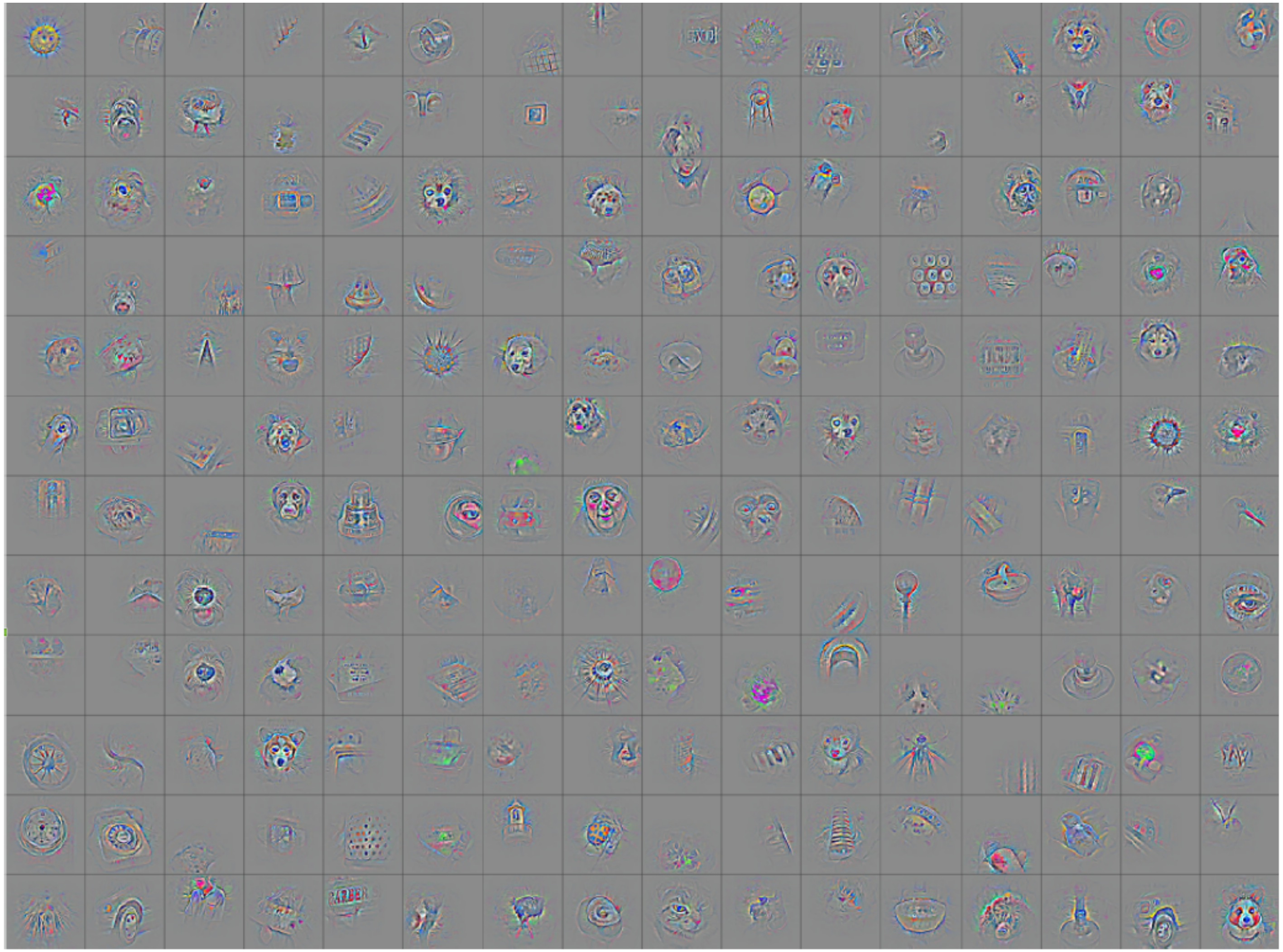
Visualizing and understanding convolutional neural networks. Zeiler, Matthew D., and Rob Fergus. *arXiv preprint arXiv:1311.2901* (2013).

Strongest activations: Stage 2



Visualizing and understanding convolutional neural networks. Zeiler, Matthew D., and Rob Fergus. *arXiv preprint arXiv:1311.2901* (2013).

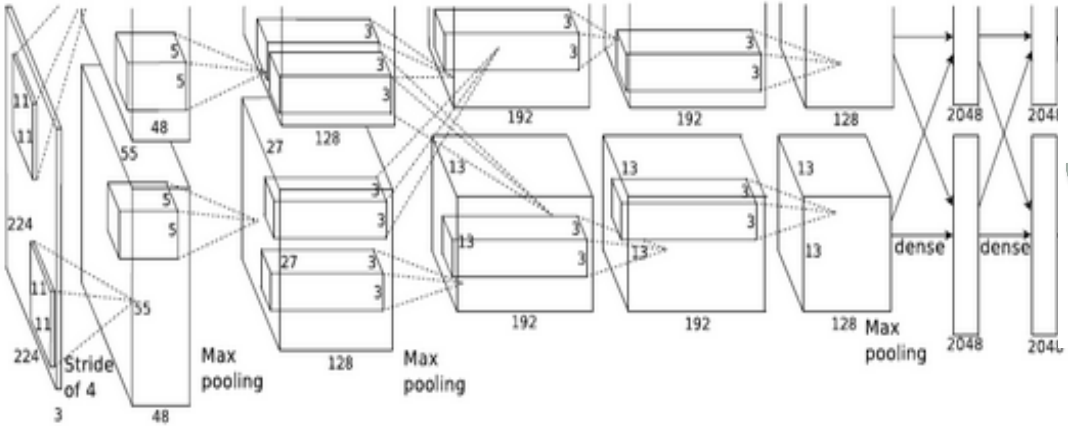
Strongest activations: Stage 5

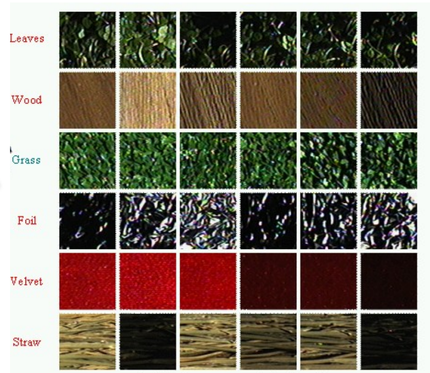


Visualizing and understanding convolutional neural networks. Zeiler, Matthew D., and Rob Fergus. *arXiv preprint arXiv:1311.2901* (2013).

CNN for features extraction and image texture recognition

Novel image to be classified





Labelled images comprise training data

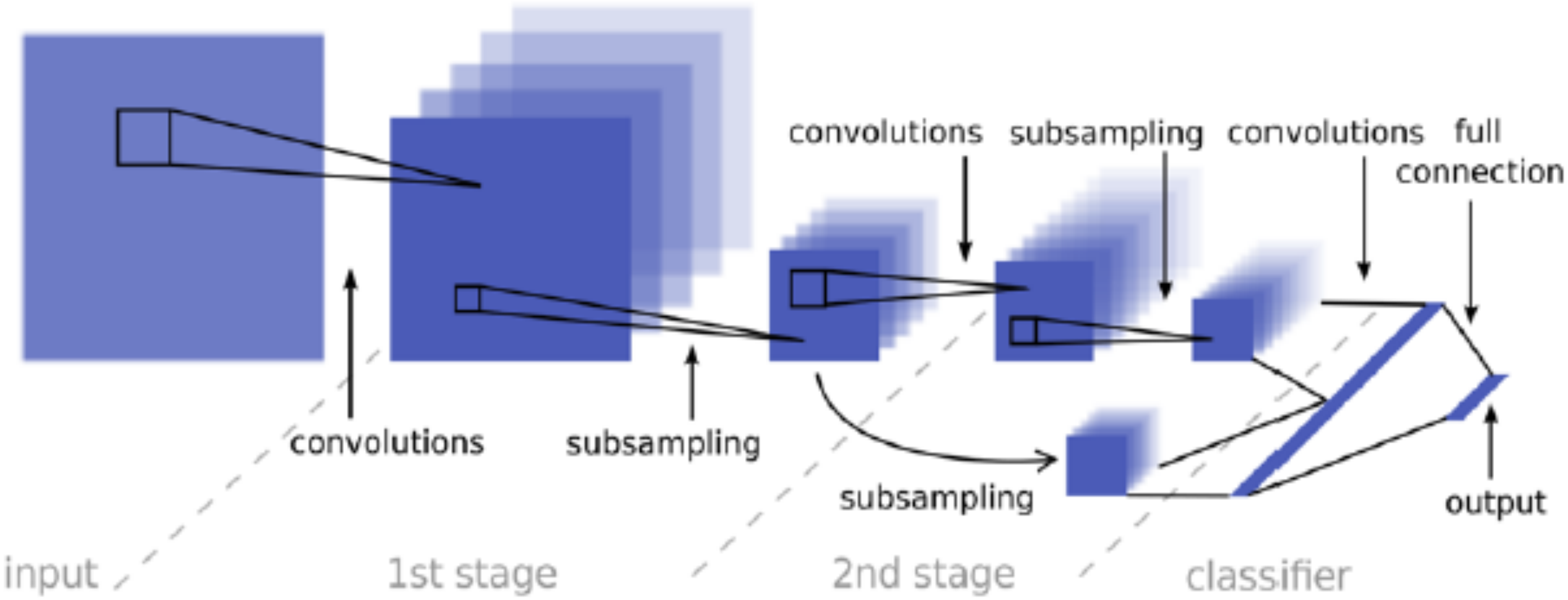
- Convolutional Neural Networks (4096 Features)
- The obtained features are used to train a classifier to recognize the images

Summary

- **Texture** is a useful property that is often indicative of materials, appearance cues.
- **Texture representations** attempt to summarize repeating patterns of local structure
- **Filter banks** useful to measure redundant variety of structures in local neighborhood
  - Feature spaces can be multi-dimensional
- **LBP** are fast, compact and illumination invariant texture descriptors.
- CNN provide powerful features for image scene (based on texture and objects) recognition.
- A lot of **texture applications** to other CV problems and real applications.

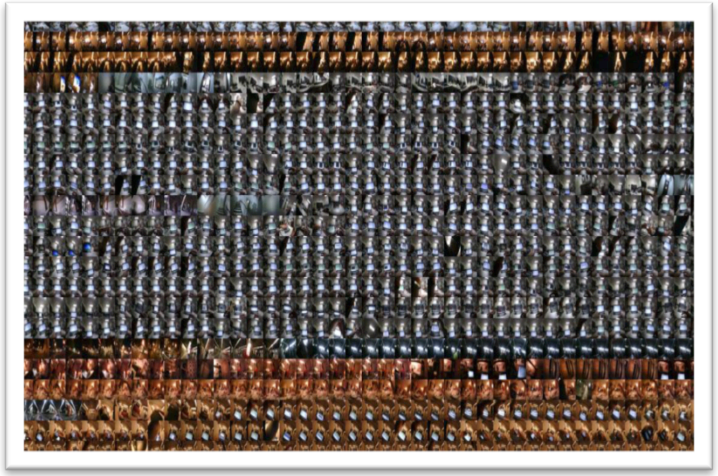
Opportunity for master thesis:

- **What is the optimal architecture of a convolutional neural network for specific problem:**
  - **Activity recognition**
  - **Event recognition**



Opportunity for master thesis:

- **From visual lifelogging to event recognition**



Opportunity for master thesis:

- **TIC applied to health:** From visual lifelogging to memorable moments extraction for mild cognitive impairment patients