# Texture: statistical models of vision

Somewhere in Cinque Terre, May 2005

CS180: Intro to Computer Vision and Comp. Photo

Alexei Efros, UC Berkeley, Fall 2024

# What is Texture?

- Texture depicts spatially repeating patterns
- Many natural phenomena are textures

radishes

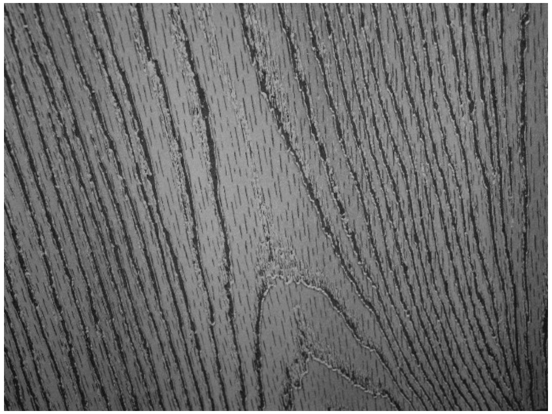
rocks

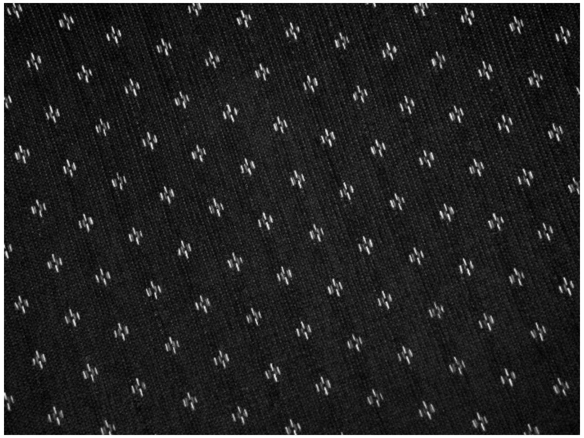
yogurt

# Texture as “stuff”

Source: Forsyth

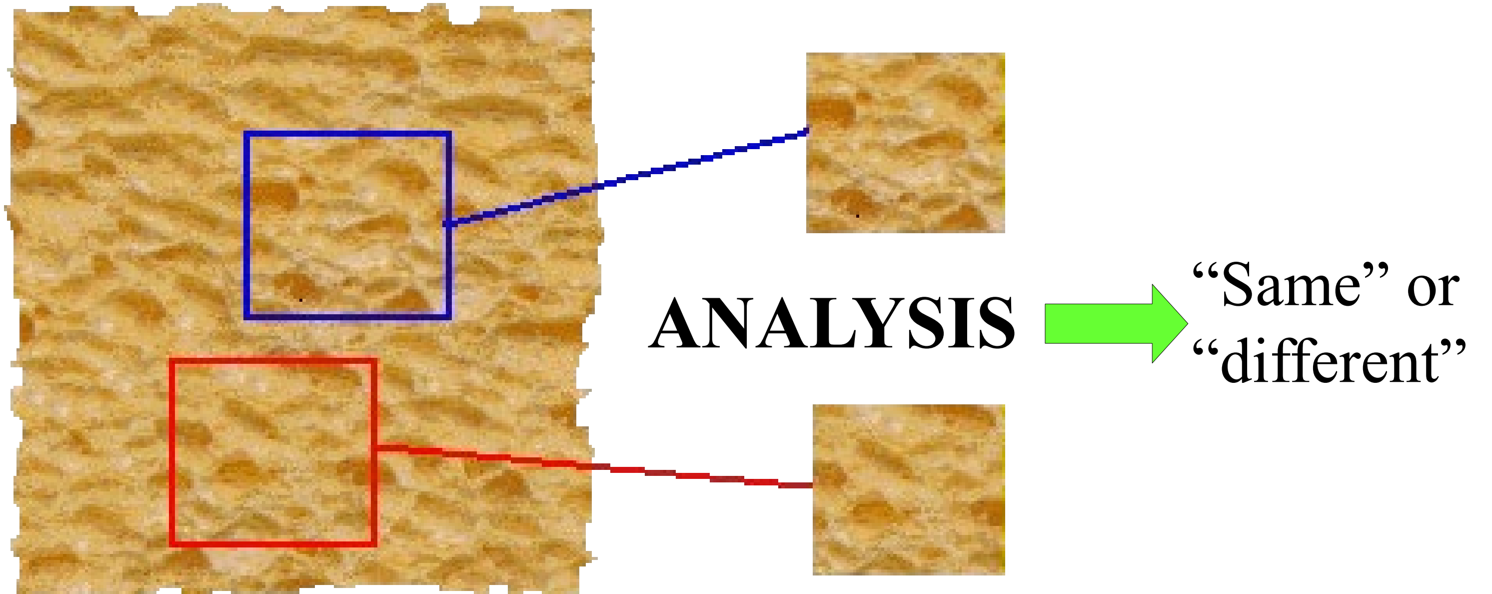
# Texture and Material





http://www-cvr.ai.uiuc.edu/ponce_grp/data/texture_database/samples/

# Texture Analysis

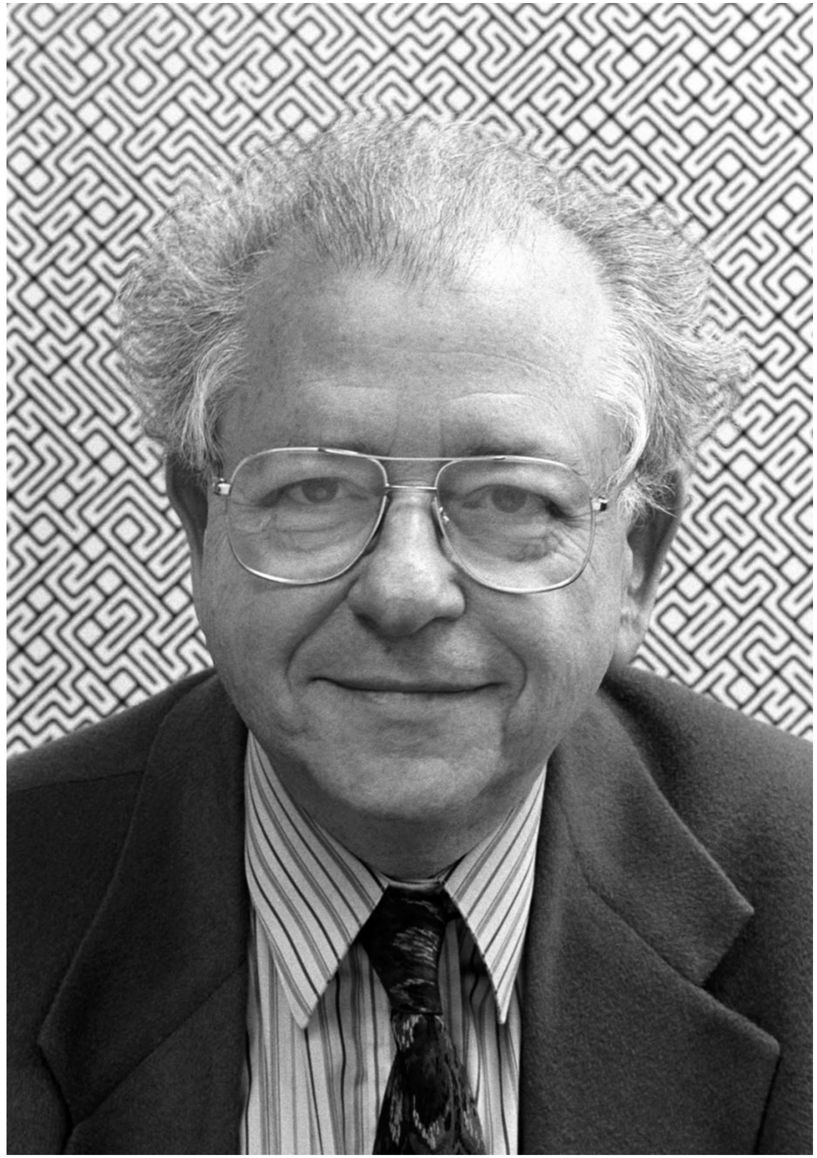



*True (infinite) texture*

Compare textures and decide if they're made of the same "stuff".

# When are two textures similar?

# Béla Julesz, father of texture



*Nature* Vol. 290 12 March 1981



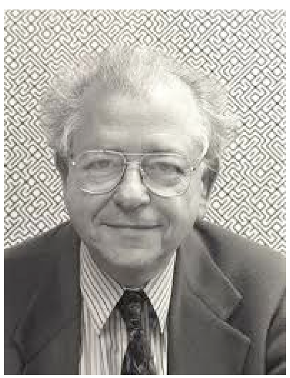
REVIEW ARTICLES

# Textons, the elements of texture perception, and their interactions

**Bela Julesz**

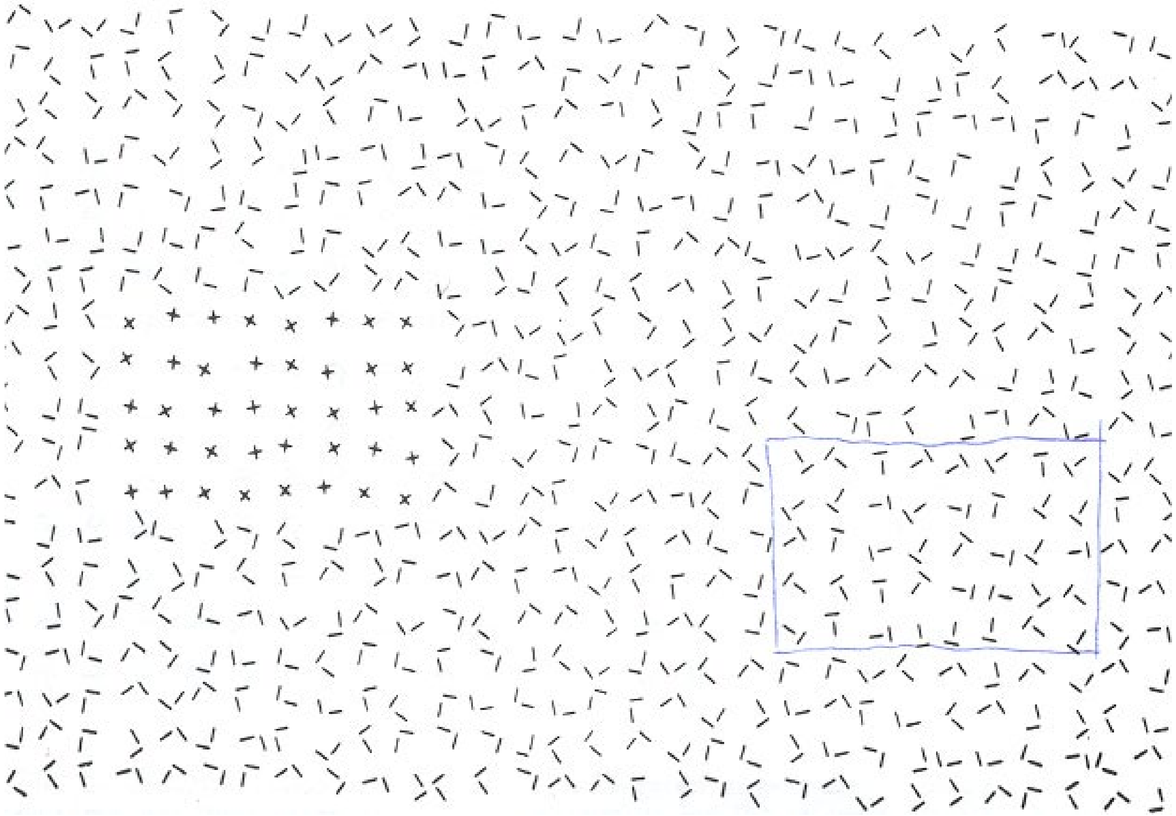
Bell Laboratories, Murray Hill, New Jersey 07974, USA

*Research with texture pairs having identical second-order statistics has revealed that the pre-attentive texture discrimination system cannot globally process third- and higher-order statistics, and that discrimination is the result of a few local conspicuous features, called textons. It seems that only the first-order statistics of these textons have perceptual significance, and the relative phase between textons cannot be perceived without detailed scrutiny by focal attention.*



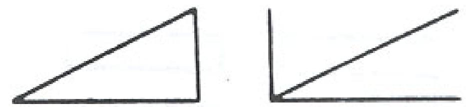
Bela Julesz, "Textons, the Elements of Texture Perception, and their Interactions". Nature 290: 91-97. March, 1981.

# Texton Discrimination (Julesz)

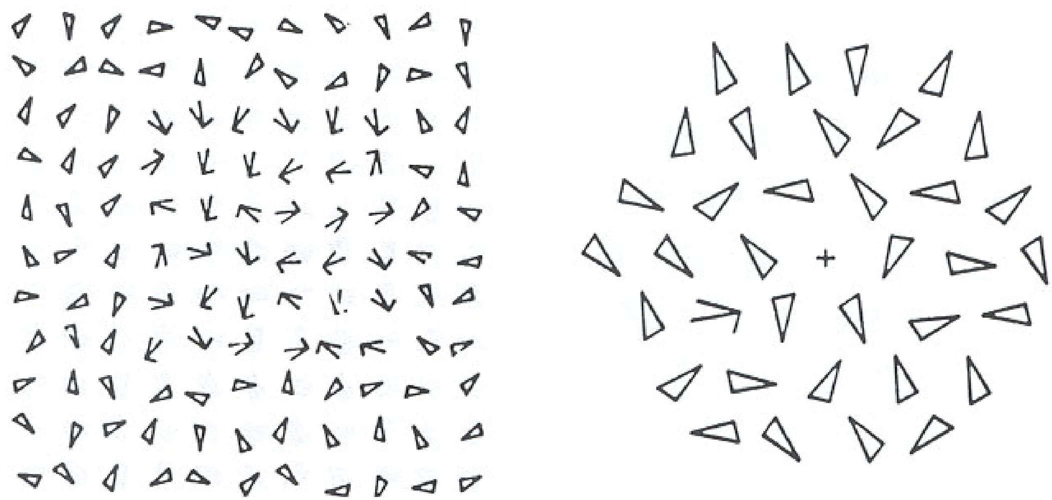


Human vision is sensitive to the difference of some types of elements and appears to be “numb” on other types of differences.

# Search Experiment I

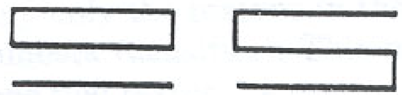


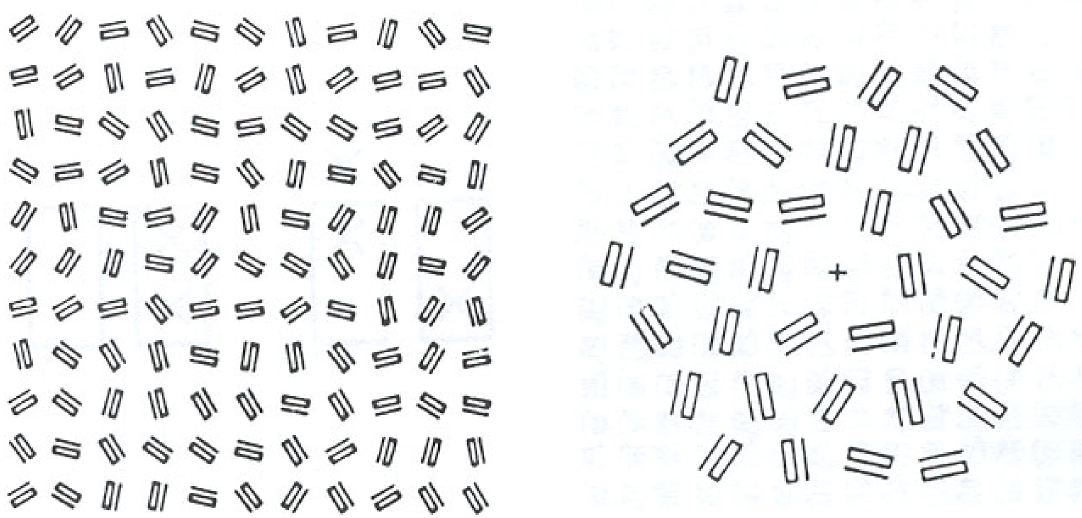
(a)



The subject is told to detect a target element in a number of background elements.
In this example, the detection time is independent of the number of background elements.

# Search Experiment II


(a)



In this example, the detection time is proportional to the number of background elements,
And thus suggests that the subject is doing element-by-element scrutiny.

# Preattentive vs Attentive Vision (Julesz)

Human vision operates in two distinct modes:

**1. Preattentive vision**

parallel, instantaneous *(~100--200ms),* without scrutiny, independent of the number of patterns, covering a large visual field.

**2. Attentive vision**

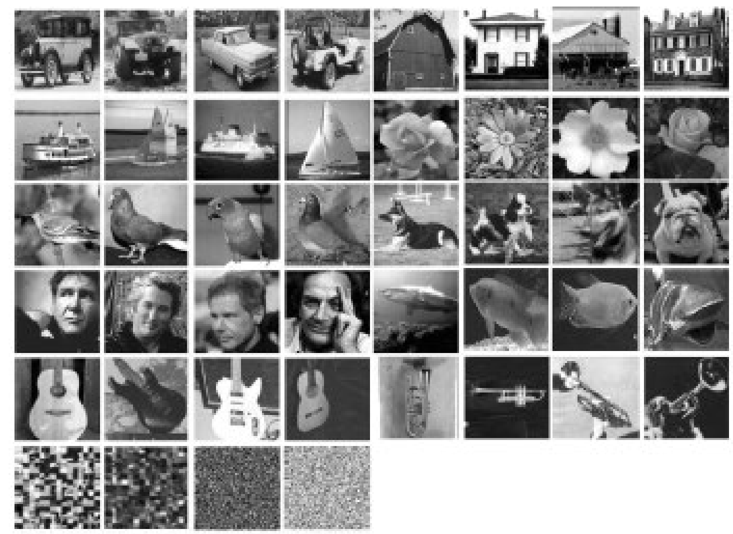
serial search by focal attention in 50ms steps limited to small aperture.

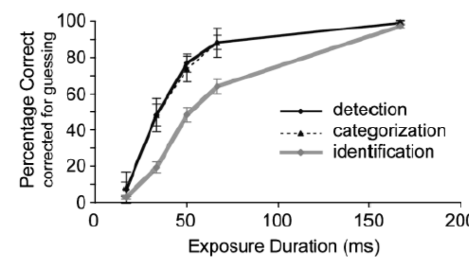
# Evidence for Pre-attentive Recognition (Thorpe)

On a task of judging **animal vs no animal**, humans can make mostly correct saccades in 150 ms (Kirchner & Thorpe, 2006)

- Comparable to synaptic delay in the retina, LGN, V1, V2, V4, IT pathway.
- Doesn't rule out feed back but shows feed forward only is very powerful

Detection and categorization are practically simultaneous (Grill-Spector & Kanwisher, 2005)

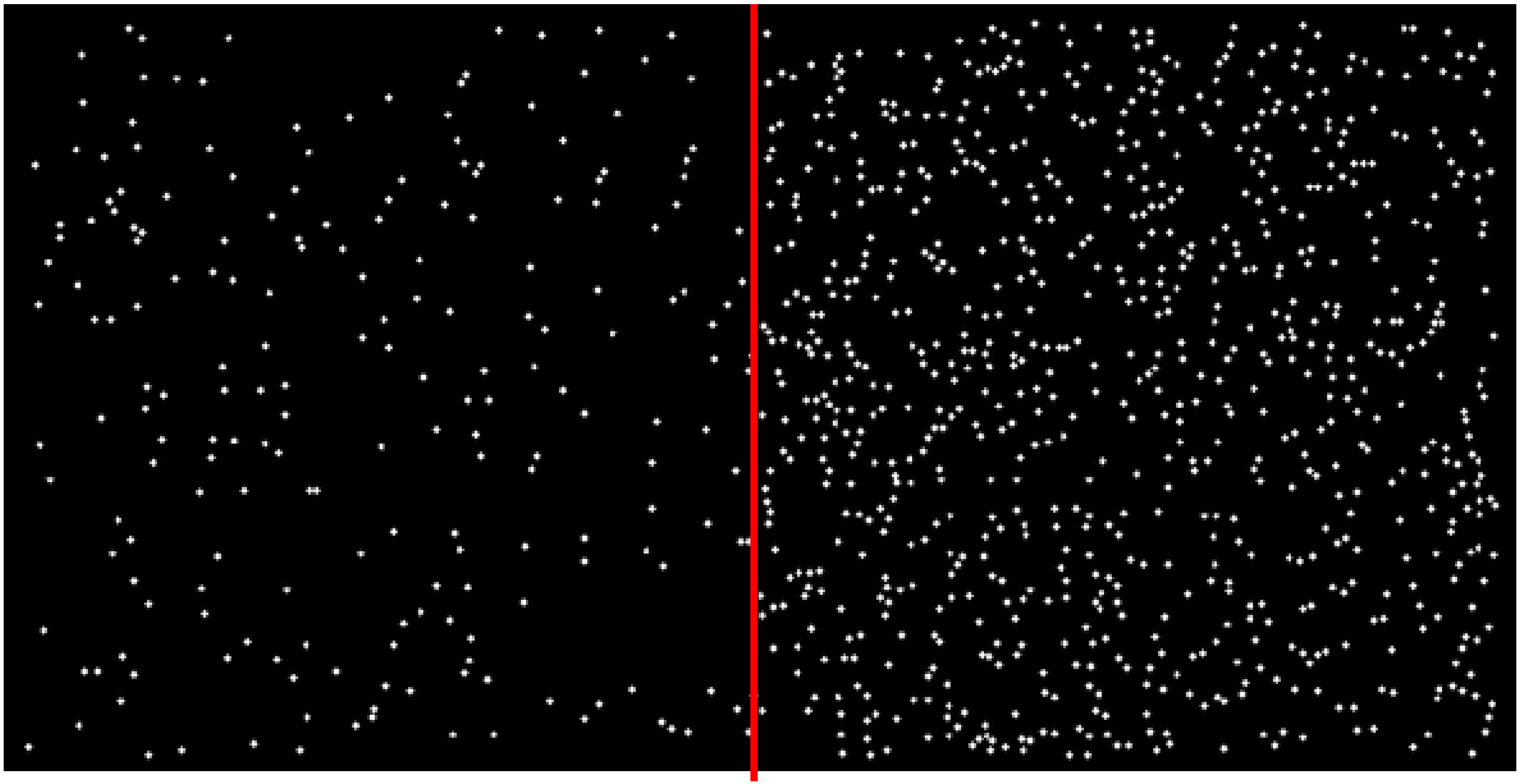




# Julesz Conjecture

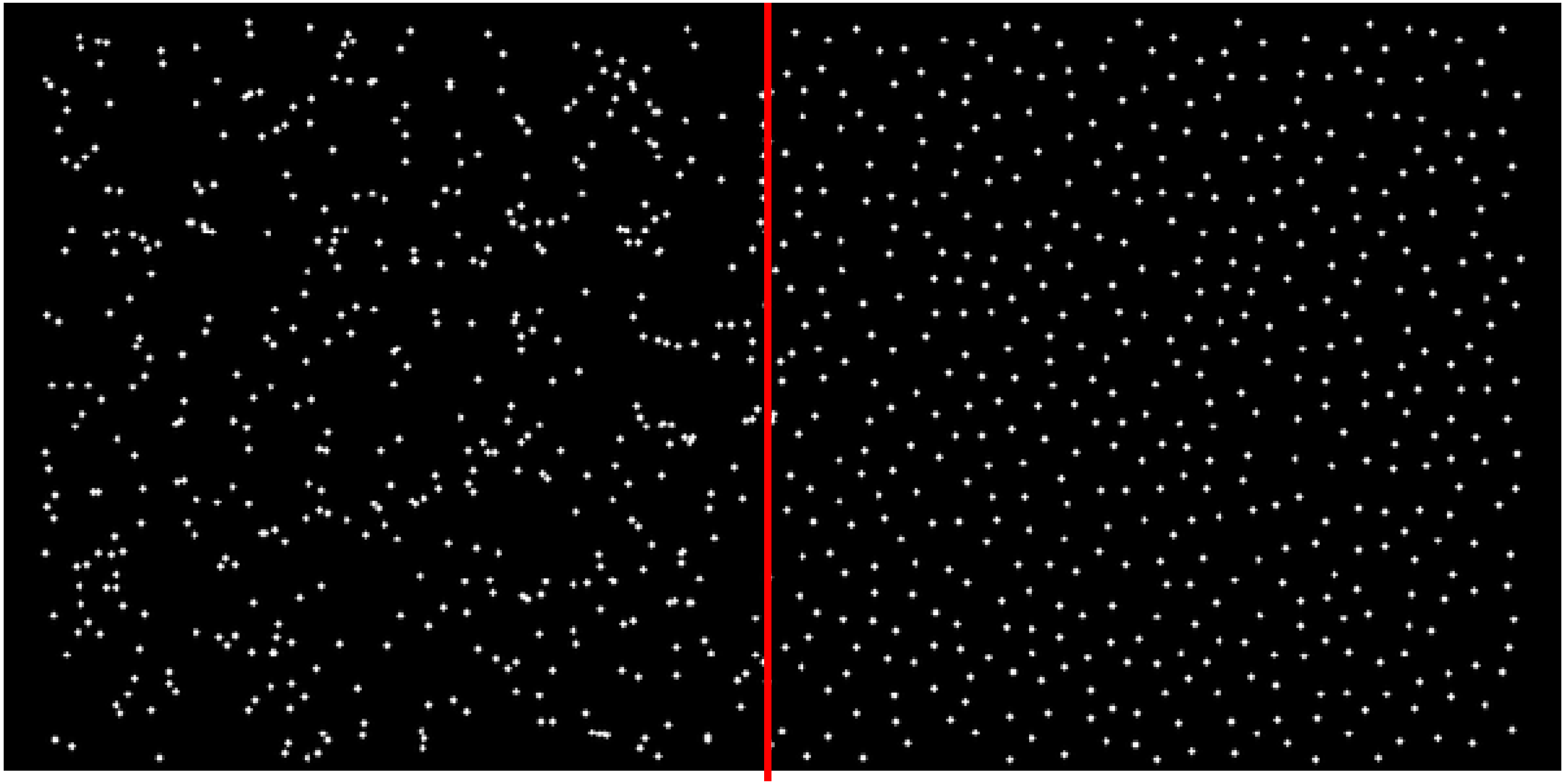
*Textures cannot be spontaneously discriminated if they have the* ***same first-order and second-order statistics*** *of texture features (textons) and differ only in their third-order or higher-order statistics.*

# 1st Order Statistics



5% white        20% white

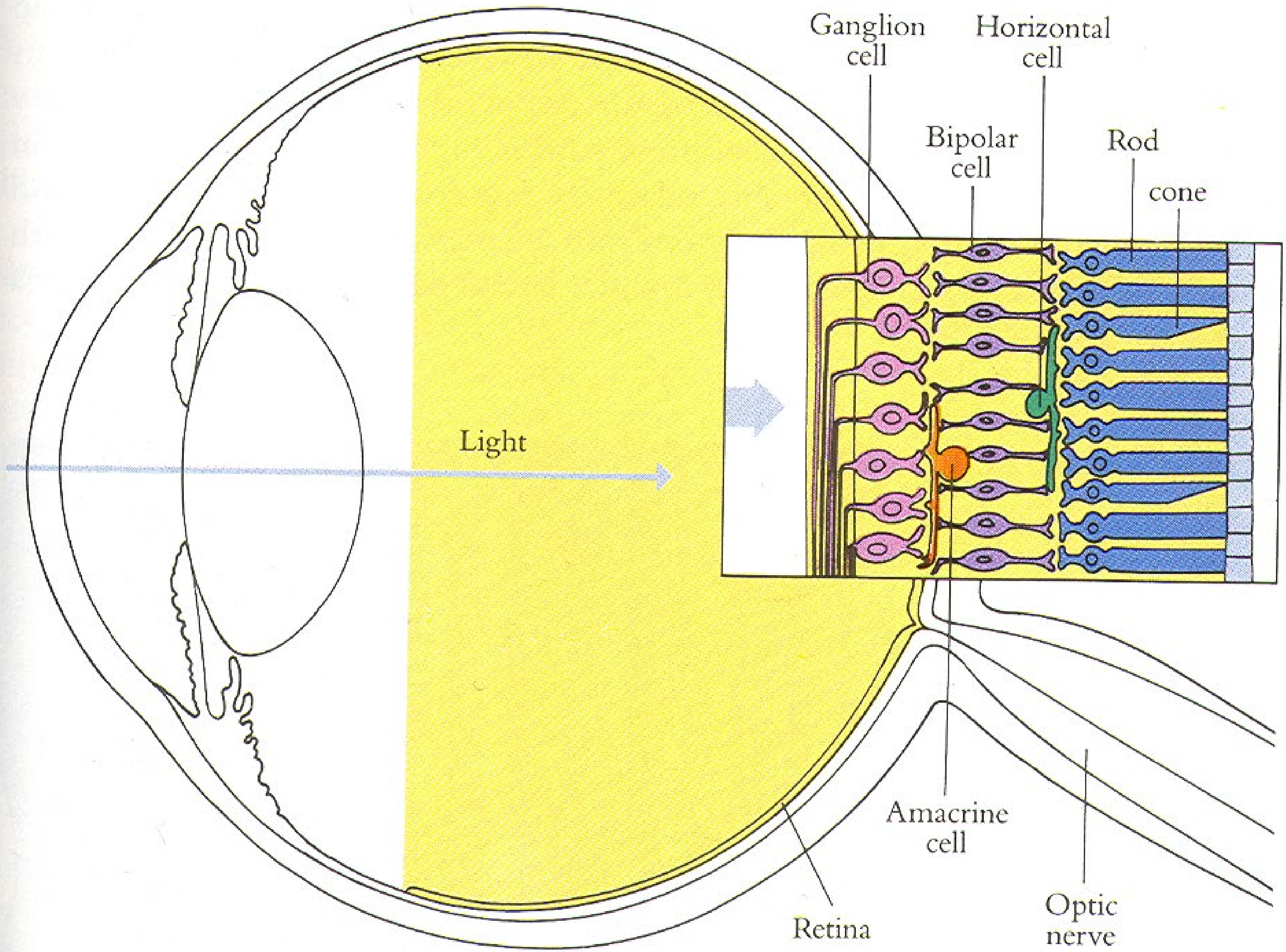
# $2^{nd}$ Order Statistics

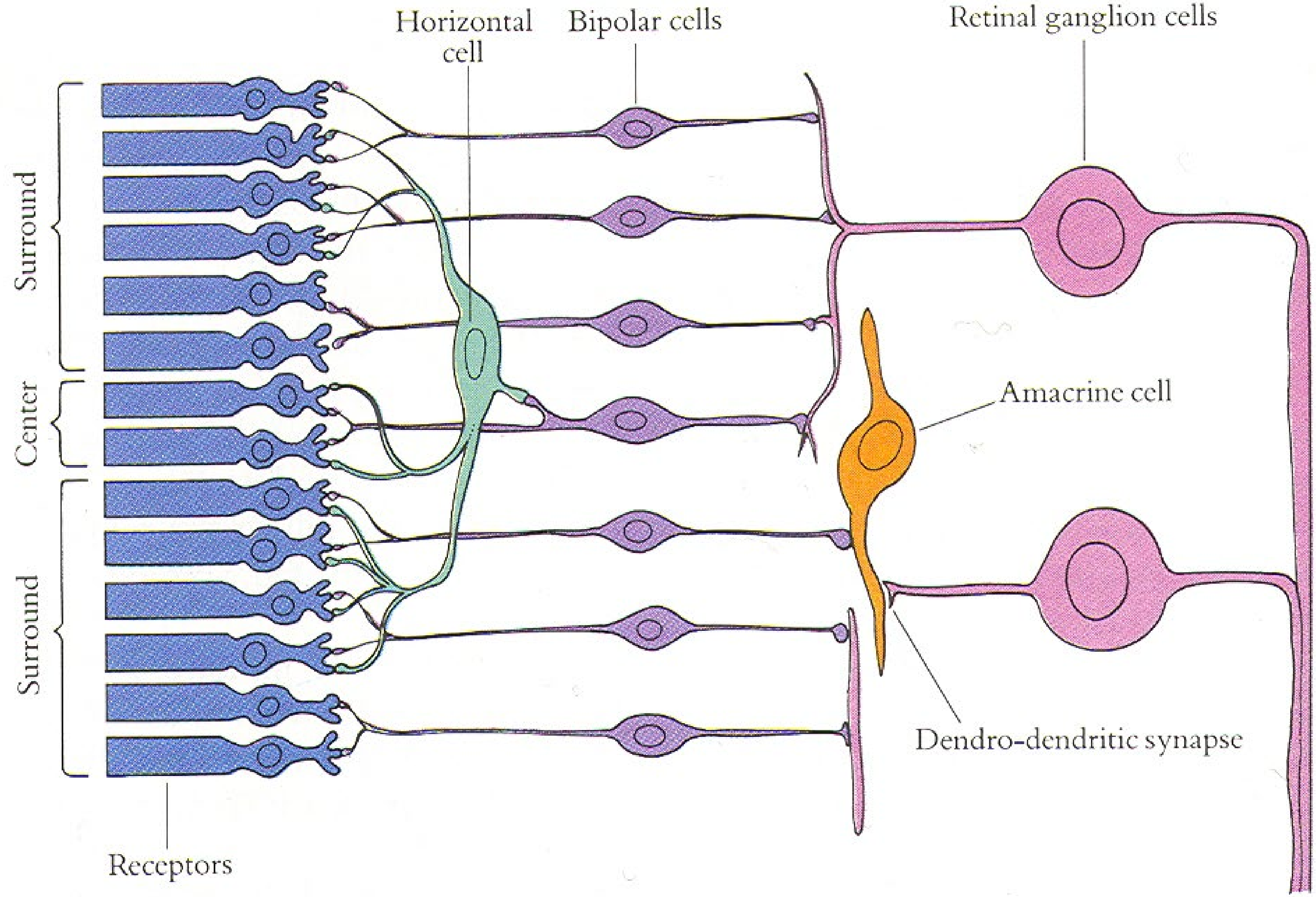


10% white

# Big Question

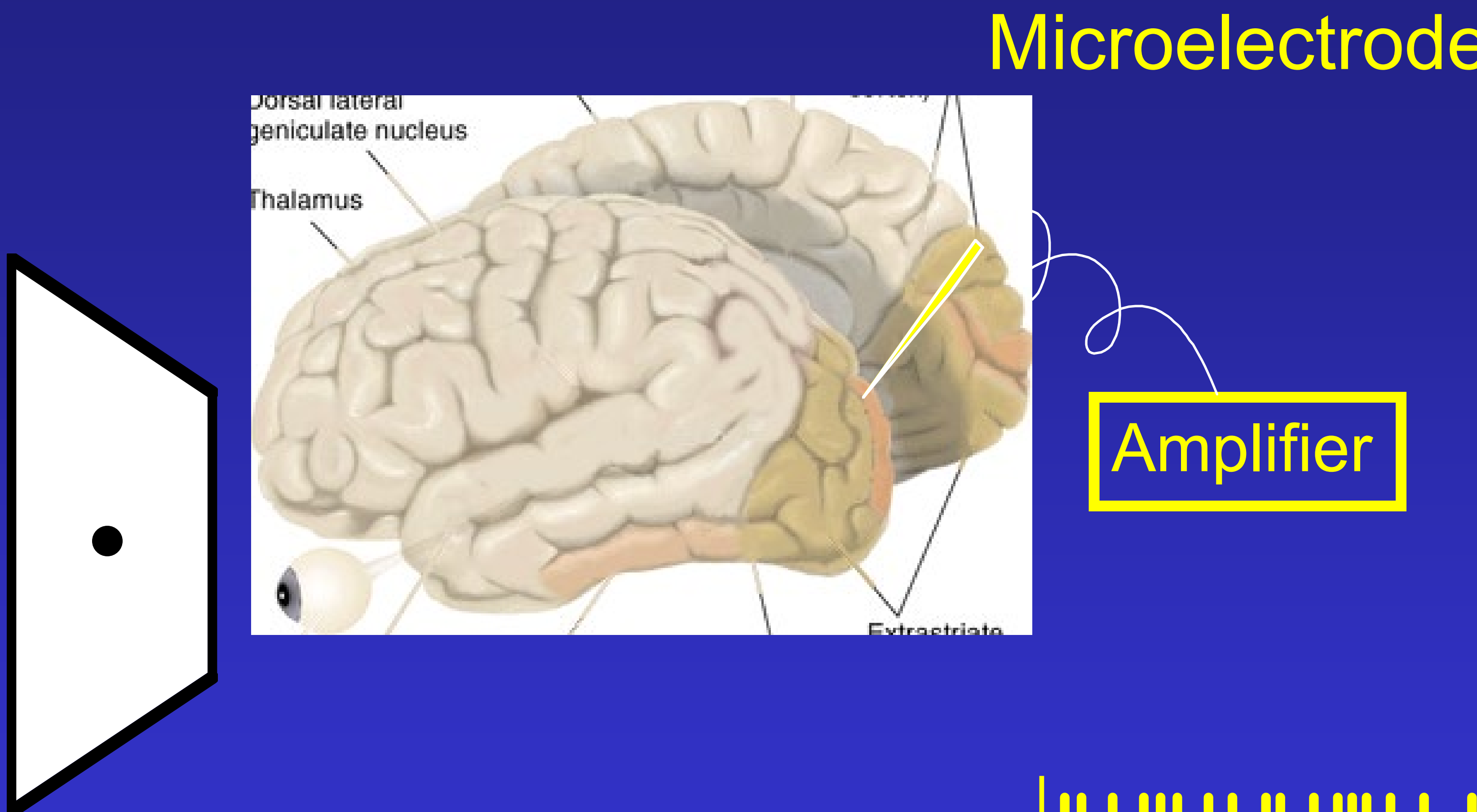
What is the statistical unit (texton) of texture in real images?


Ganglion
cell
Horizontal
cell
Bipolar
cell
Rod
cone
Light
Amacrine
cell
Retina
Optic
nerve

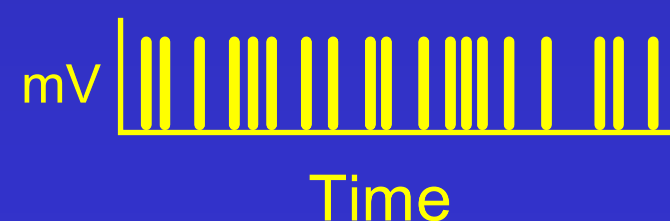

Horizontal cell
Bipolar cells
Retinal ganglion cells
Surround
Center
Surround
Amacrine cell
Dendro-dendritic synapse
Receptors

# Single Cell Recording

# Single Cell Recording



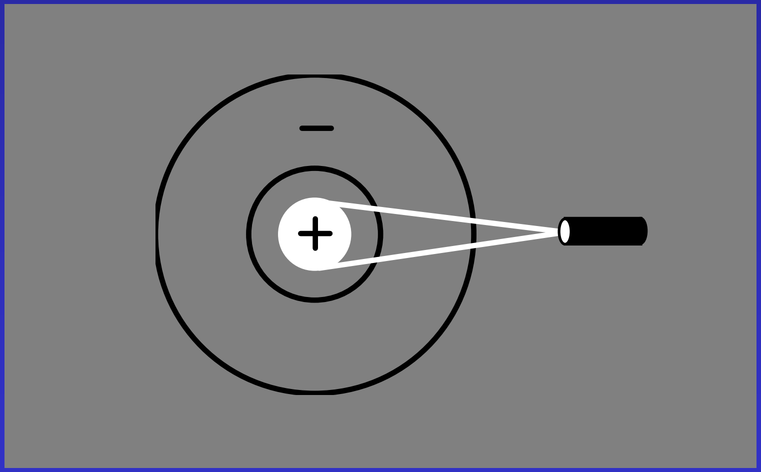

Electrical response
(action potentials)

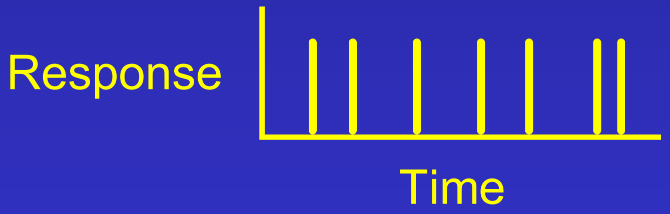


# Retinal Receptive Fields

Receptive field structure in ganglion cells:

On-center Off-surround




Stimulus condition

Electrical response

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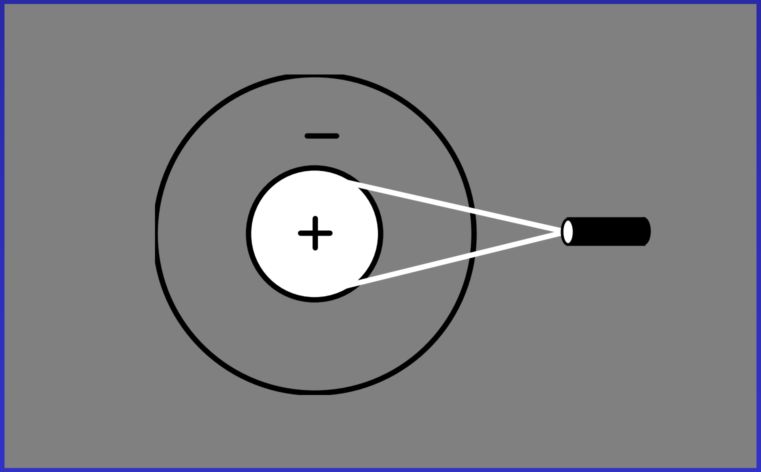
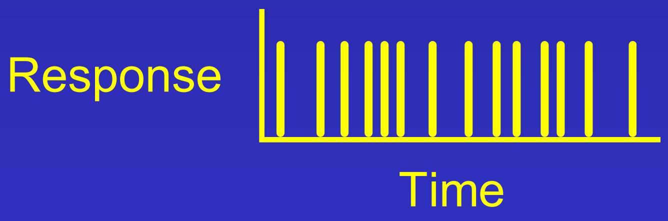



Stimulus condition




Electrical response

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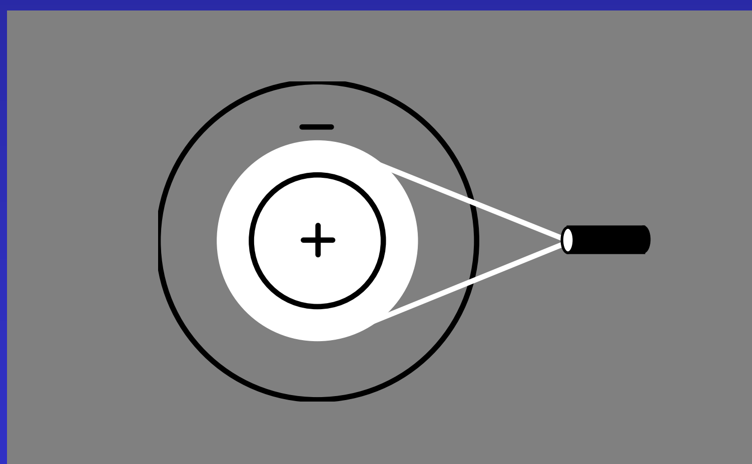


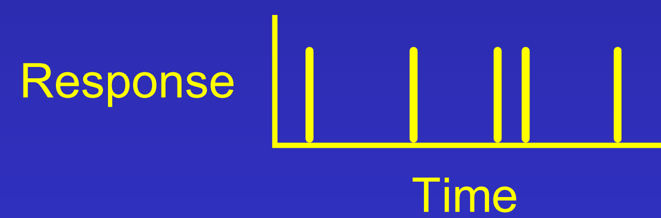


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Electrical response

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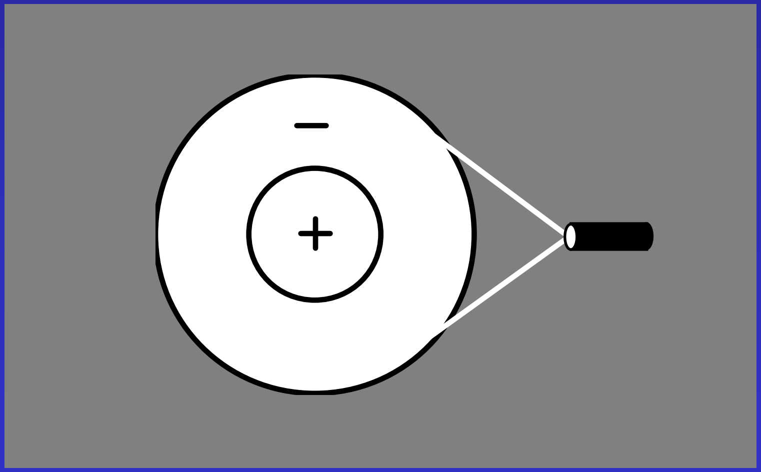


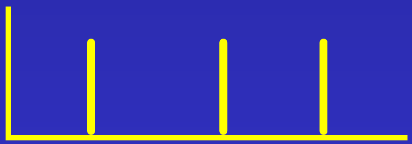


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Electrical response

# Retinal Receptive Fields

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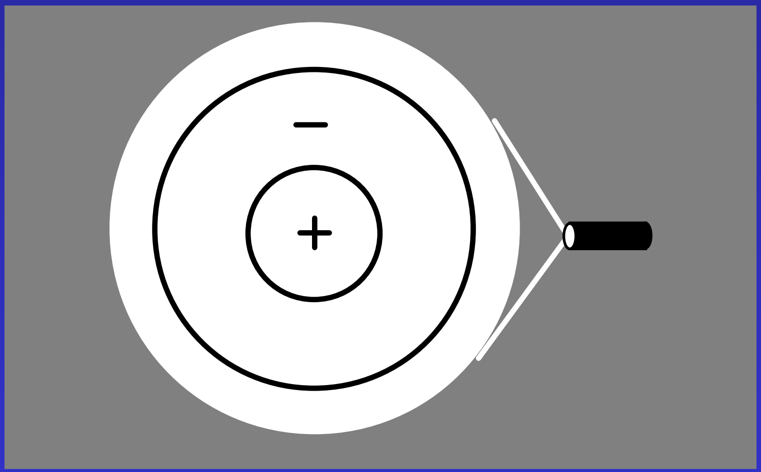


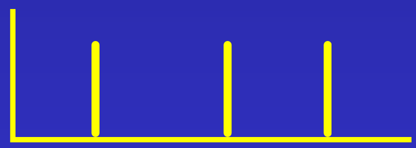


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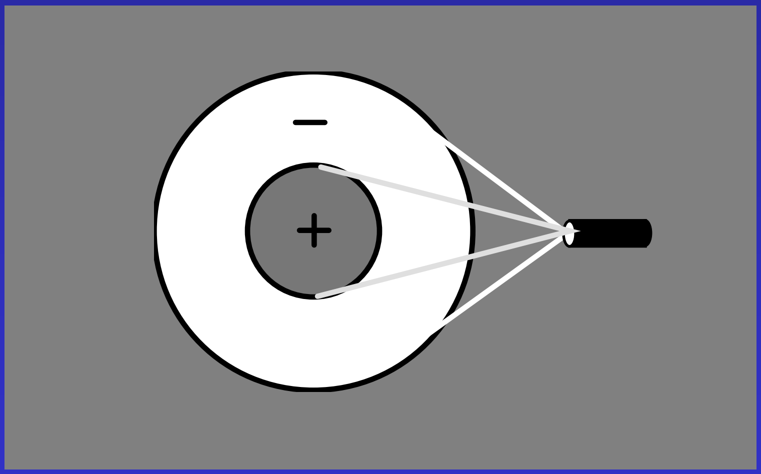
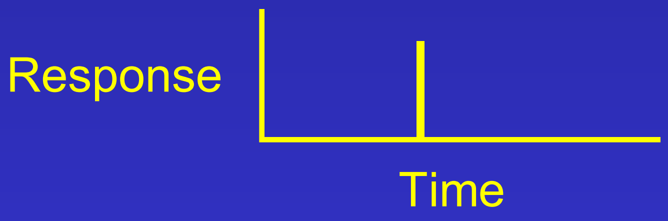


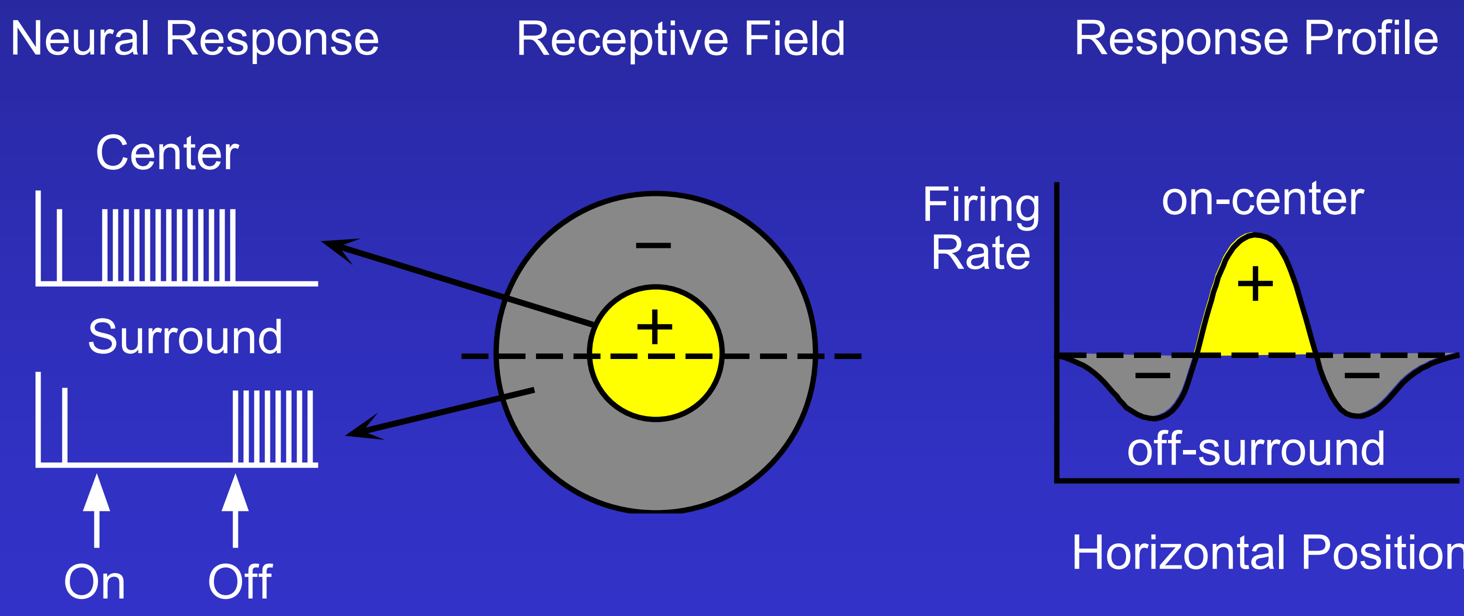




Stimulus condition

Electrical response

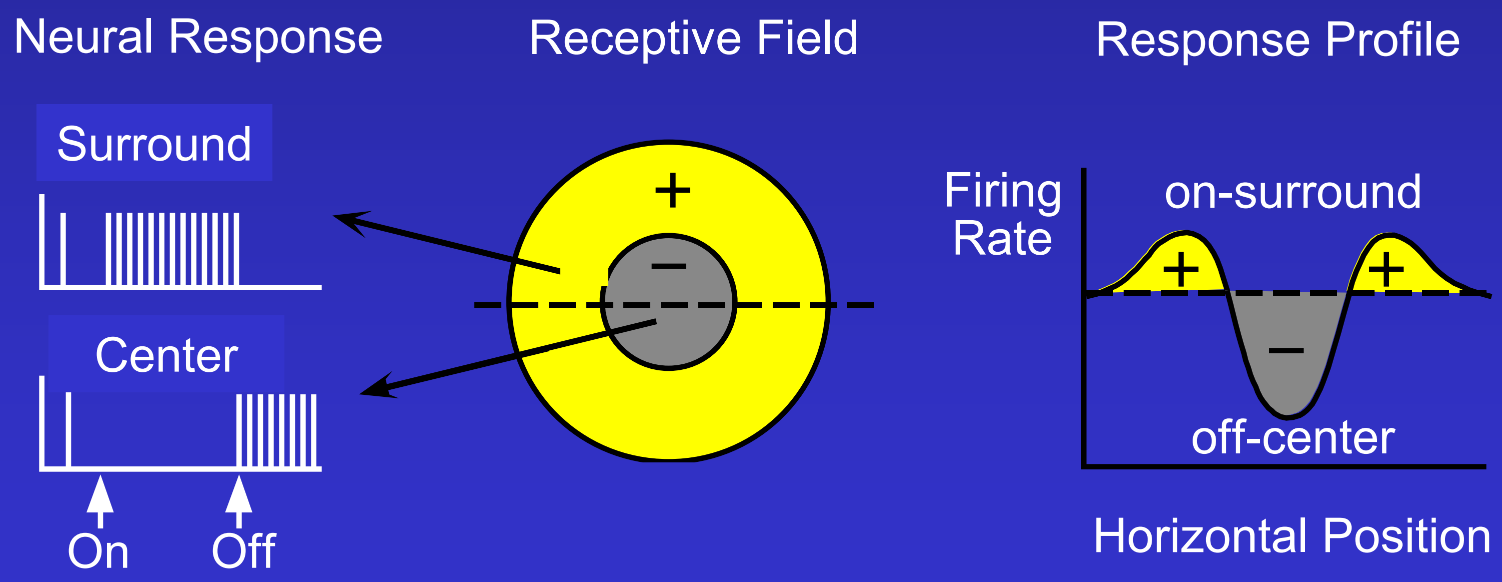
# Retinal Receptive Fields

## RF of On-center Off-surround cells

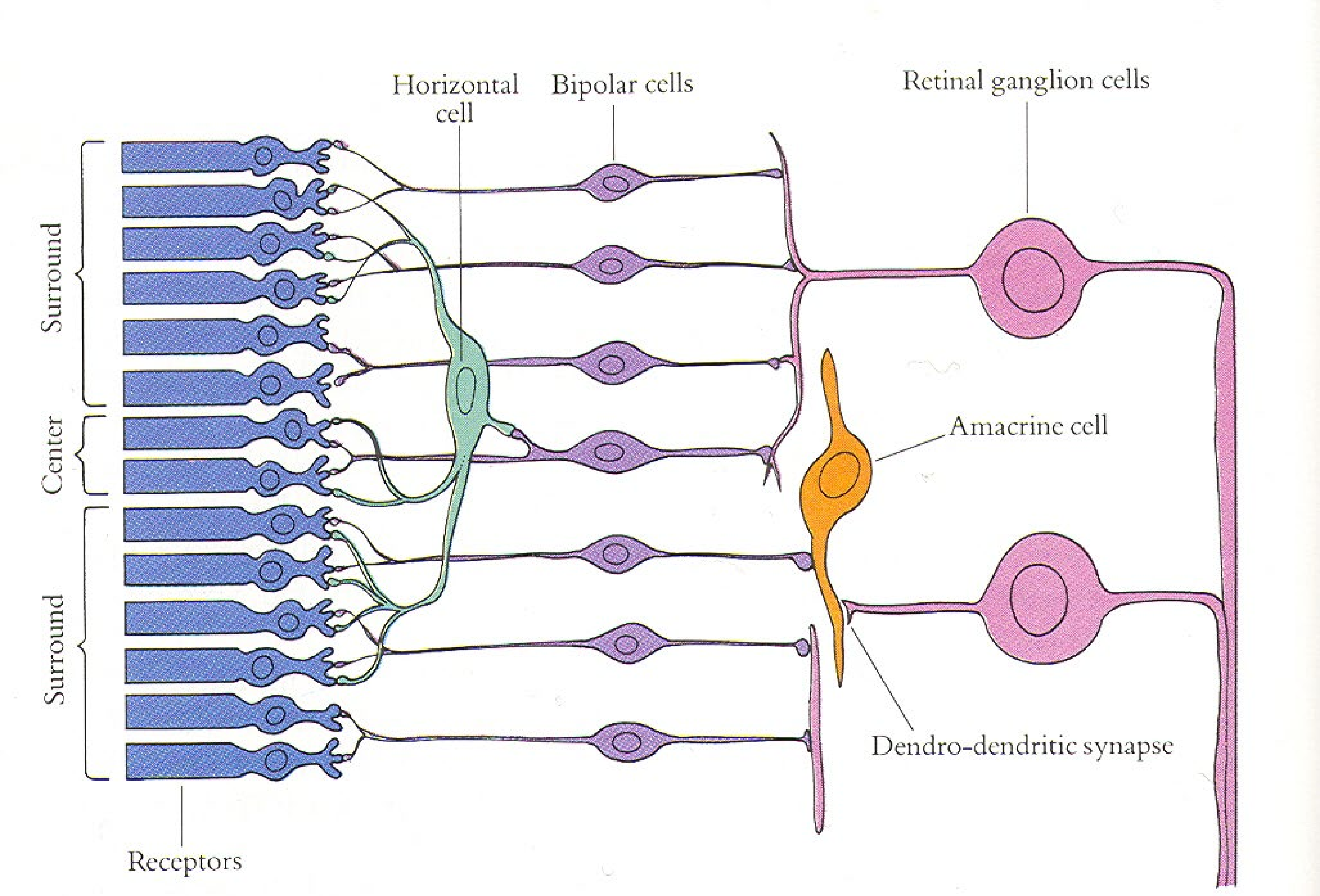


# Retinal Receptive Fields

## RF of Off-center On-surround cells

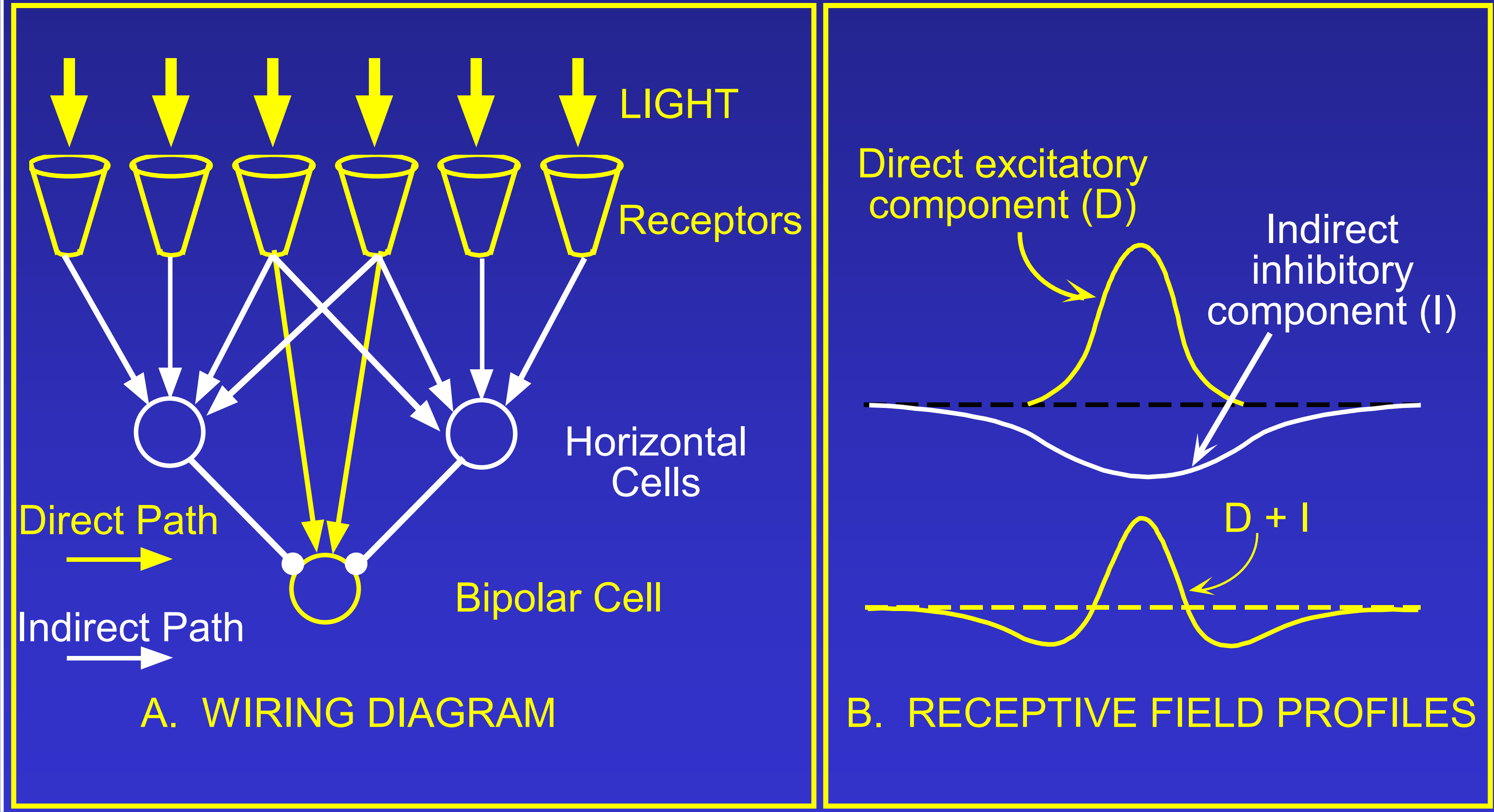


# Retinal Receptive Fields

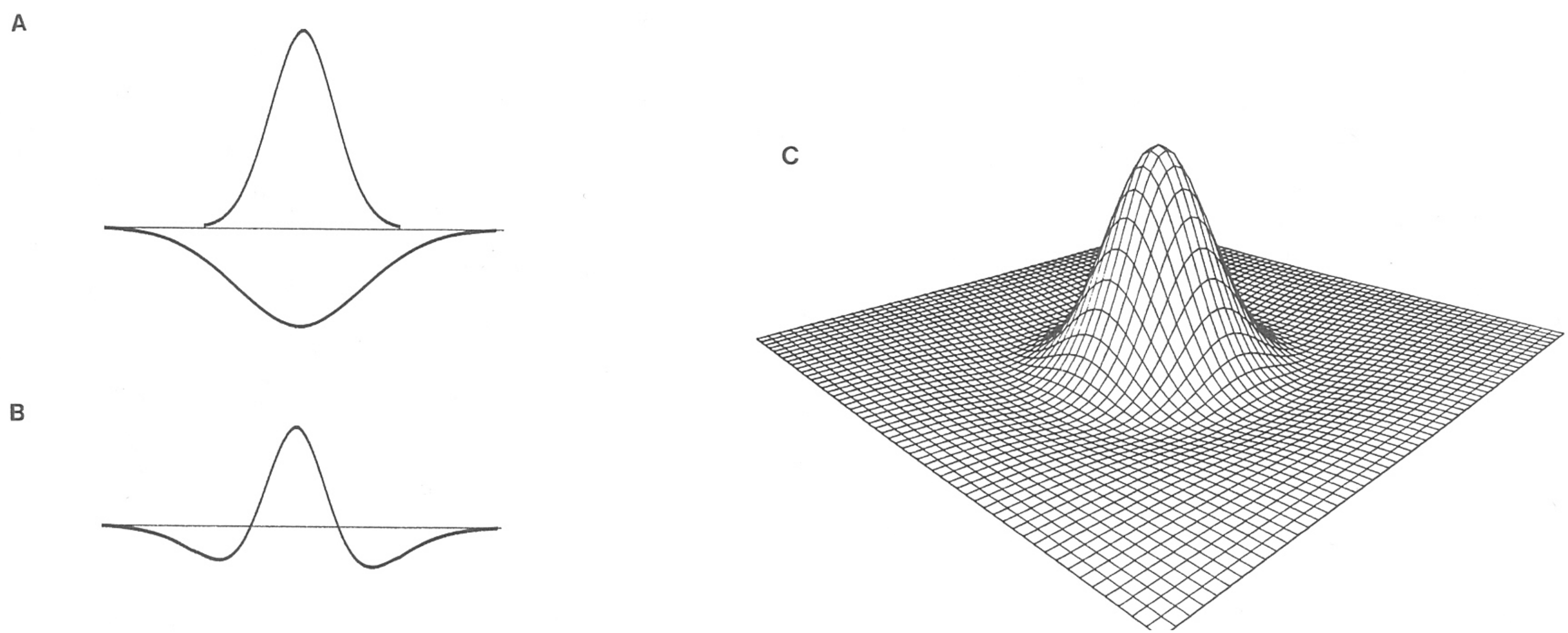


# Retinal Receptive Fields

## Receptive field structure in bipolar cells



# The receptive field of a retinal ganglion cell can be modeled as a “Difference of Gaussians”




$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}}$$

# Receptive Fields

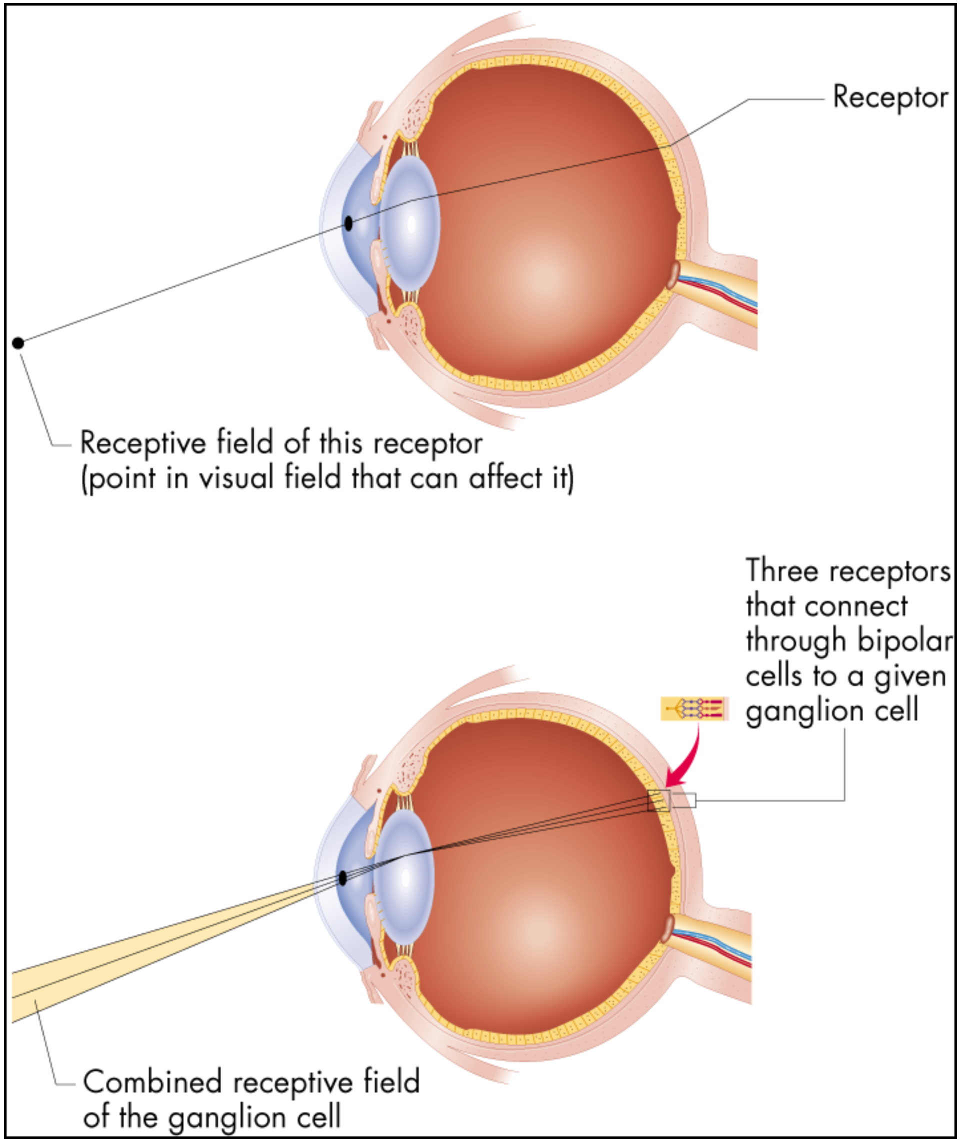
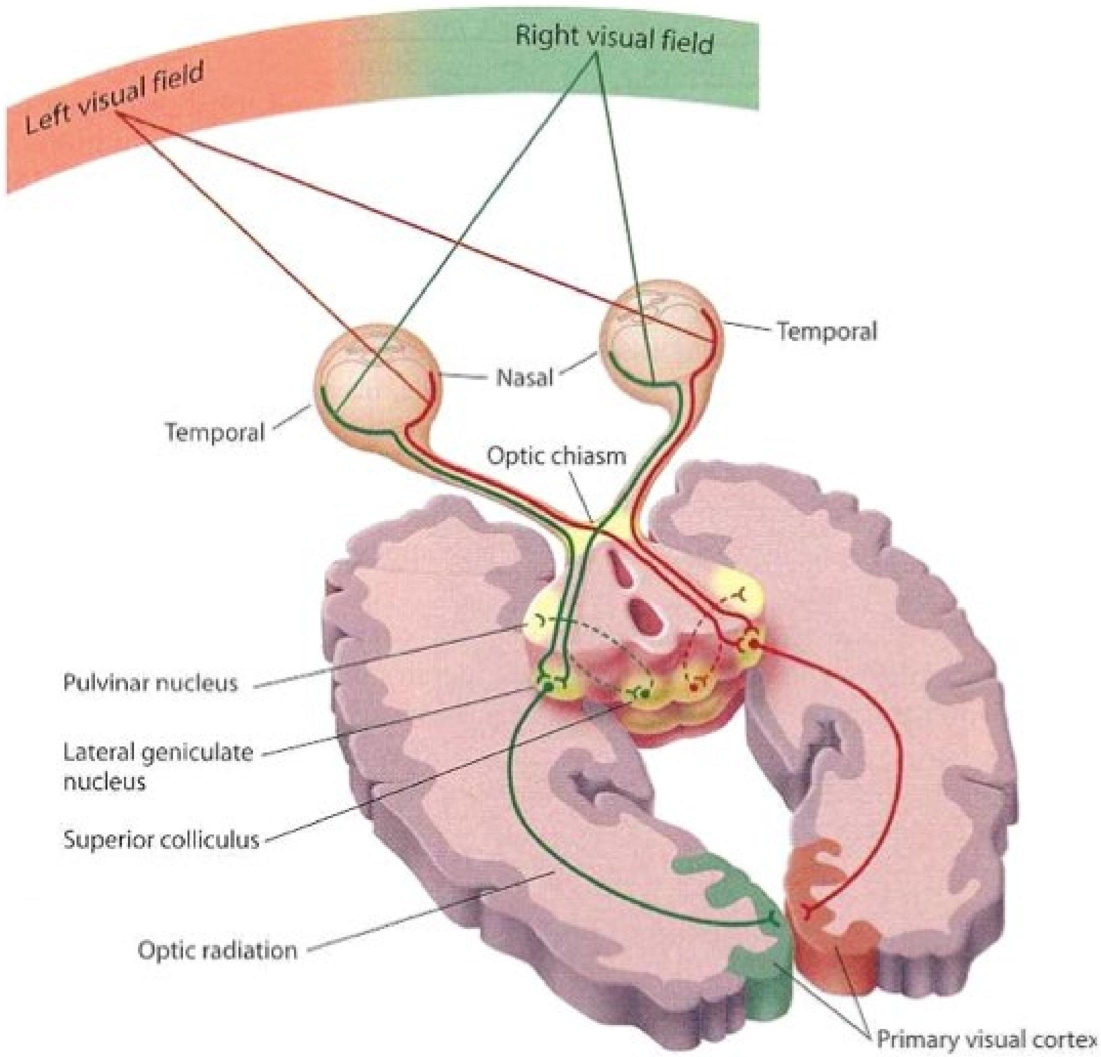



**Figure 6.16 Receptive fields**
The receptive field of a receptor is simply the area of the visual field from which light strikes that receptor. For any other cell in the visual system, the receptive field is determined by which receptors connect to the cell in question.

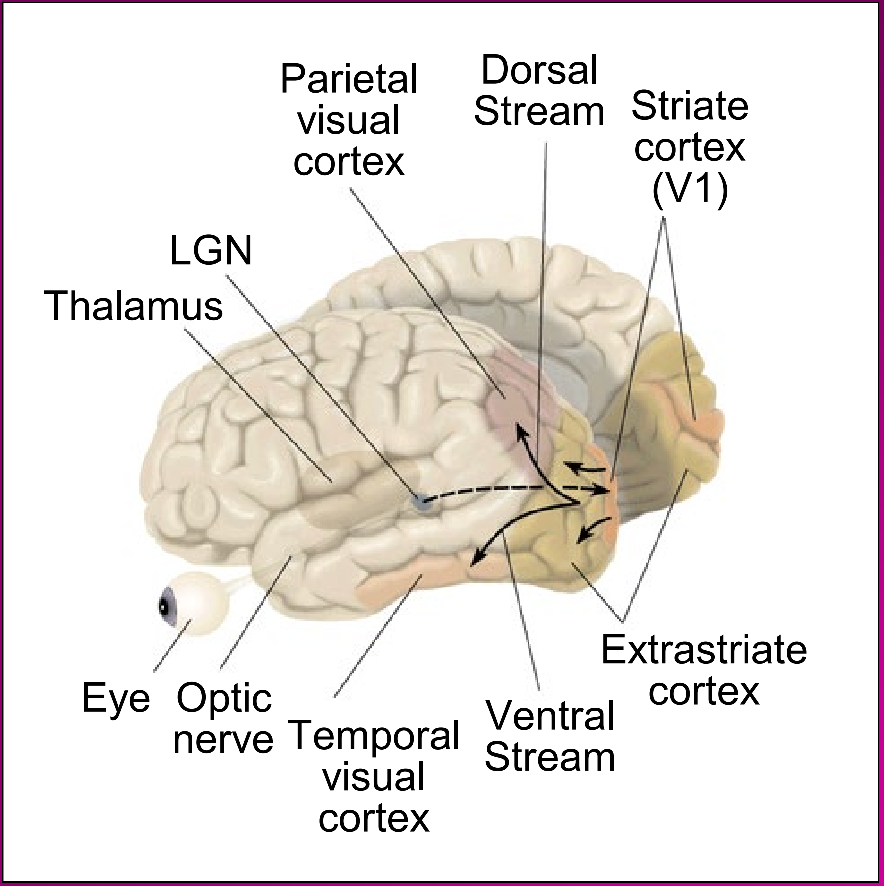
# Anatomy of Pathway to Visual Cortex



# Visual Cortex

## Cortical Area V1

aka:
Primary visual cortex
Striate cortex
Brodman's area 17



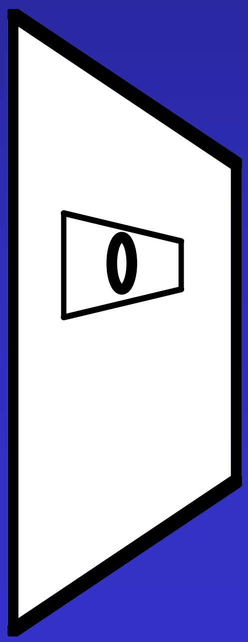
# Cortical Receptive Fields

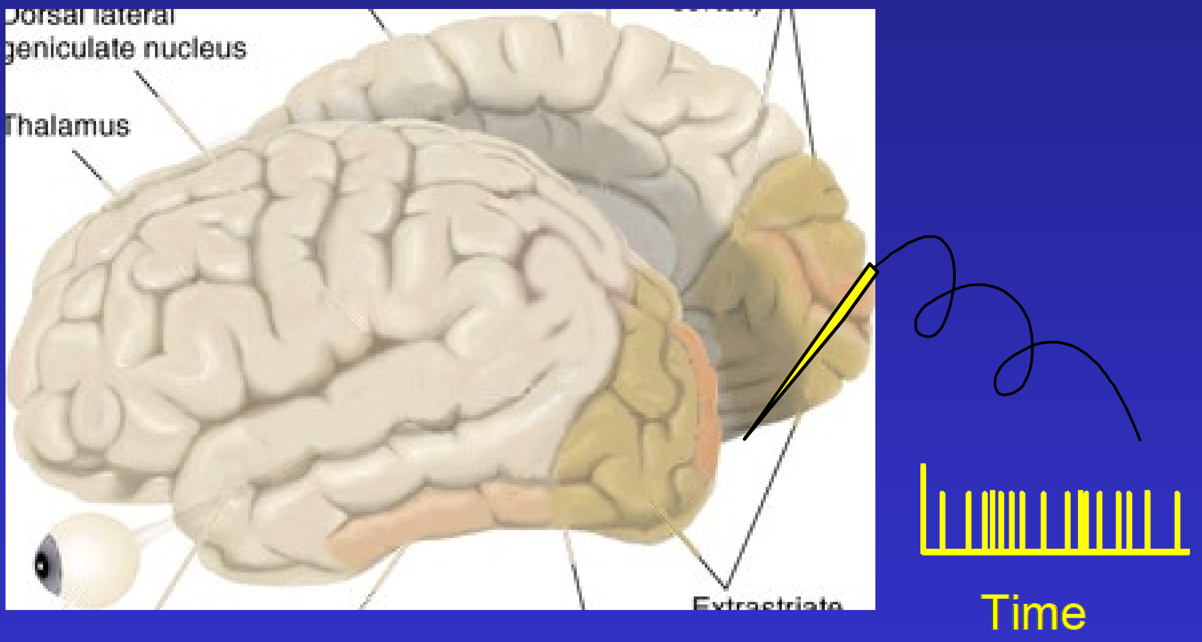
Single-cell recording from visual cortex

David Hubel & Thorston Wiesel

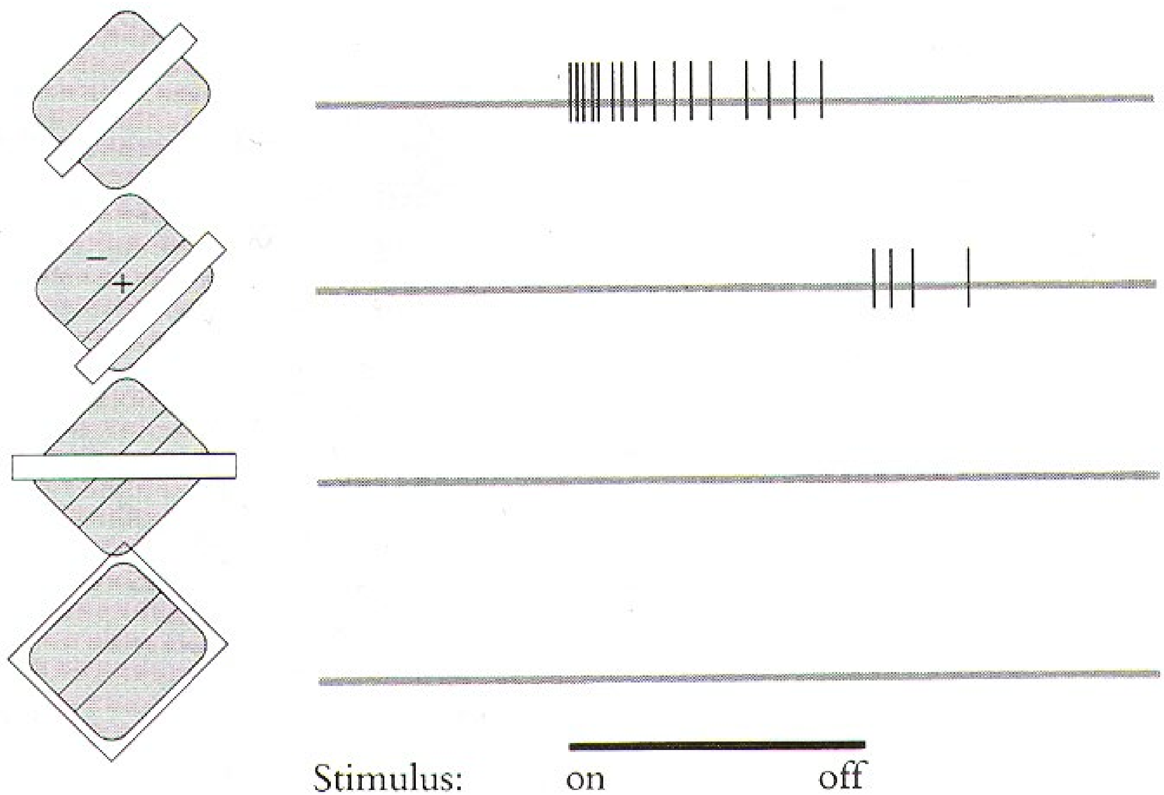
# Cortical Receptive Fields

Single-cell recording from visual cortex



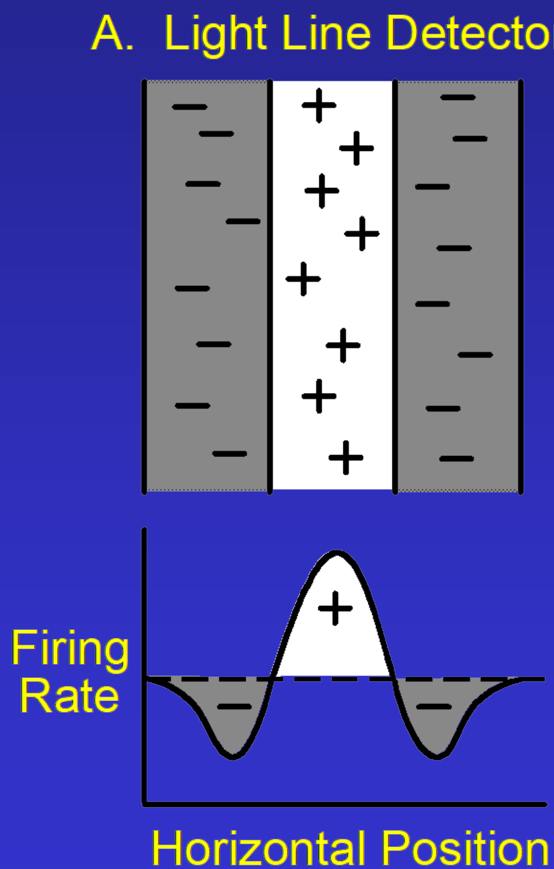


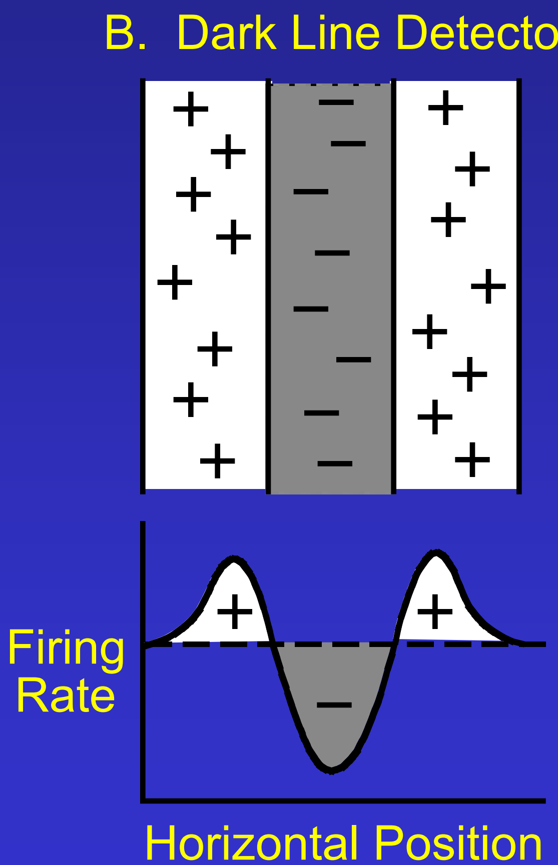
https://www.youtube.com/watch?v=IOHayh06LJ4


−
+
Stimulus:
on
off

# Cortical Receptive Fields

## Simple Cells: “Line Detectors”

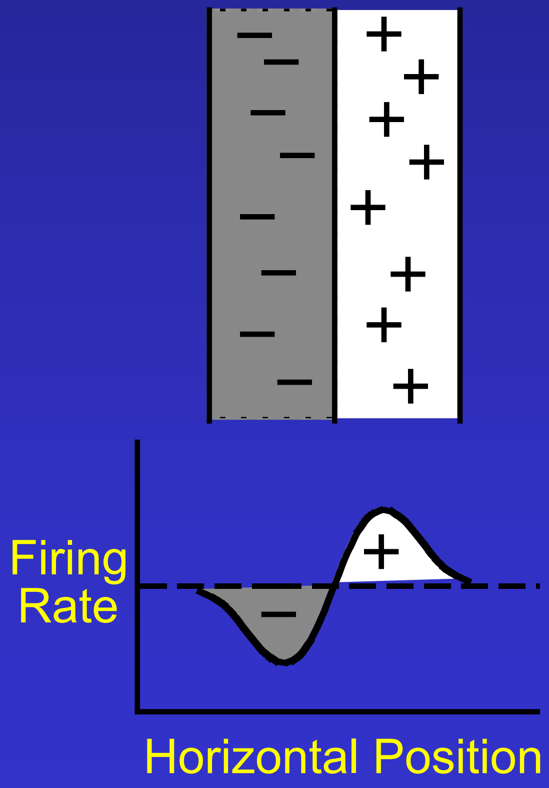


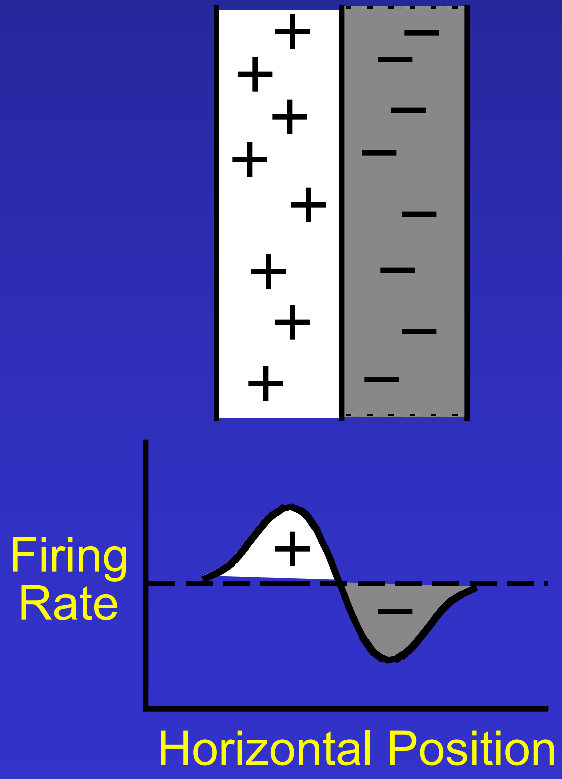
# Cortical Receptive Fields

## Simple Cells: "Edge Detectors"

C. Dark-to-light Edge Detector

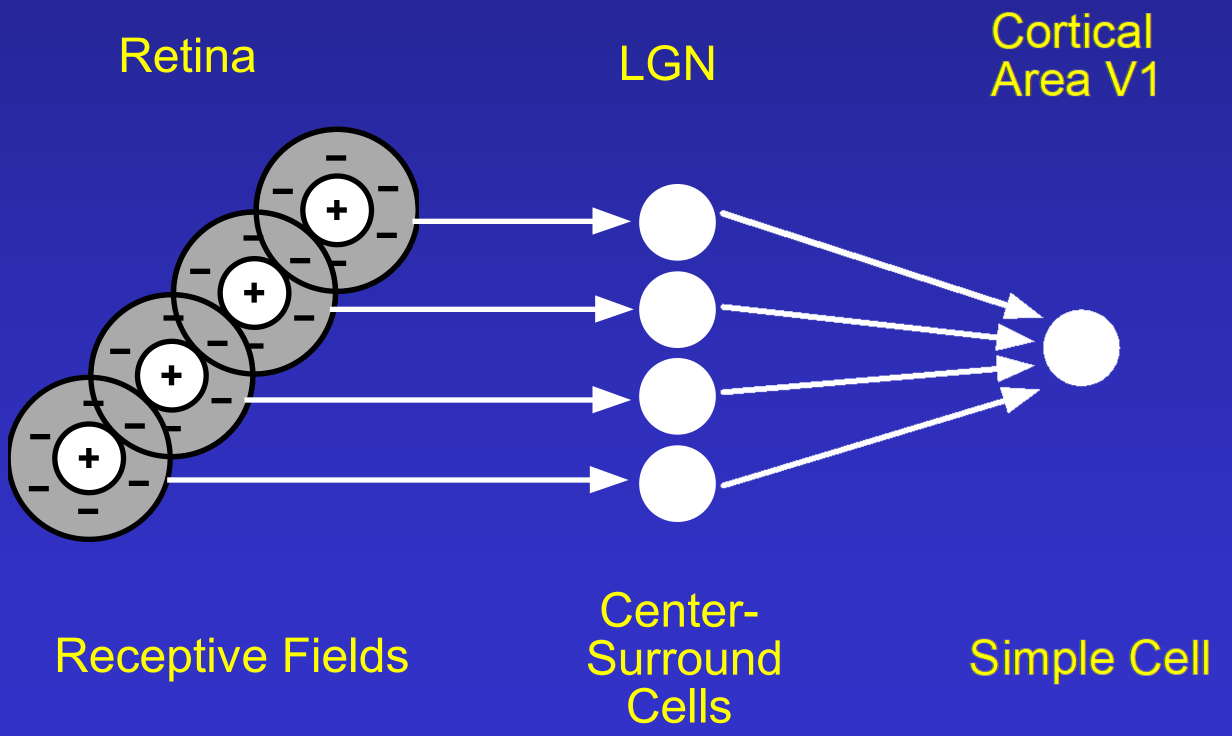



D. Light-to-dark Edge Detector

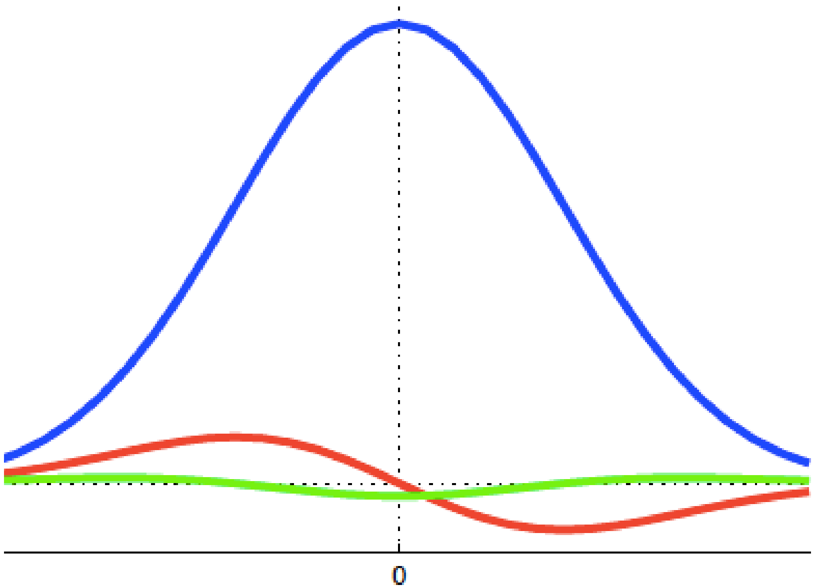


# Cortical Receptive Fields

## Constructing a line detector



# The 1D Gaussian and its derivatives




$$G_\sigma(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

$$G'_\sigma(x) = \frac{d}{dx} G_\sigma(x) = -\frac{1}{\sigma}\left(\frac{x}{\sigma}\right) G_\sigma(x)$$

$$G''_\sigma(x) = \frac{d^2}{dx^2} G_\sigma(x) = \frac{1}{\sigma^2}\left(\frac{x^2}{\sigma^2} - 1\right) G_\sigma(x)$$

$G'_\sigma(x)$'s maxima/minima occur at $G''_\sigma(x)$'s zeros. And, we can see that $G'_\sigma(x)$ is an odd symmetric function and $G''_\sigma(x)$ is an even symmetric function.

# Oriented Gaussian Derivatives in 2D

$$f_1(x, y) = G'_{\sigma_1}(x)G_{\sigma_2}(y) \tag{10.4}$$
$$f_2(x, y) = G''_{\sigma_1}(x)G_{\sigma_2}(y) \tag{10.5}$$

We also consider rotated versions of these Gaussian derivative functions.

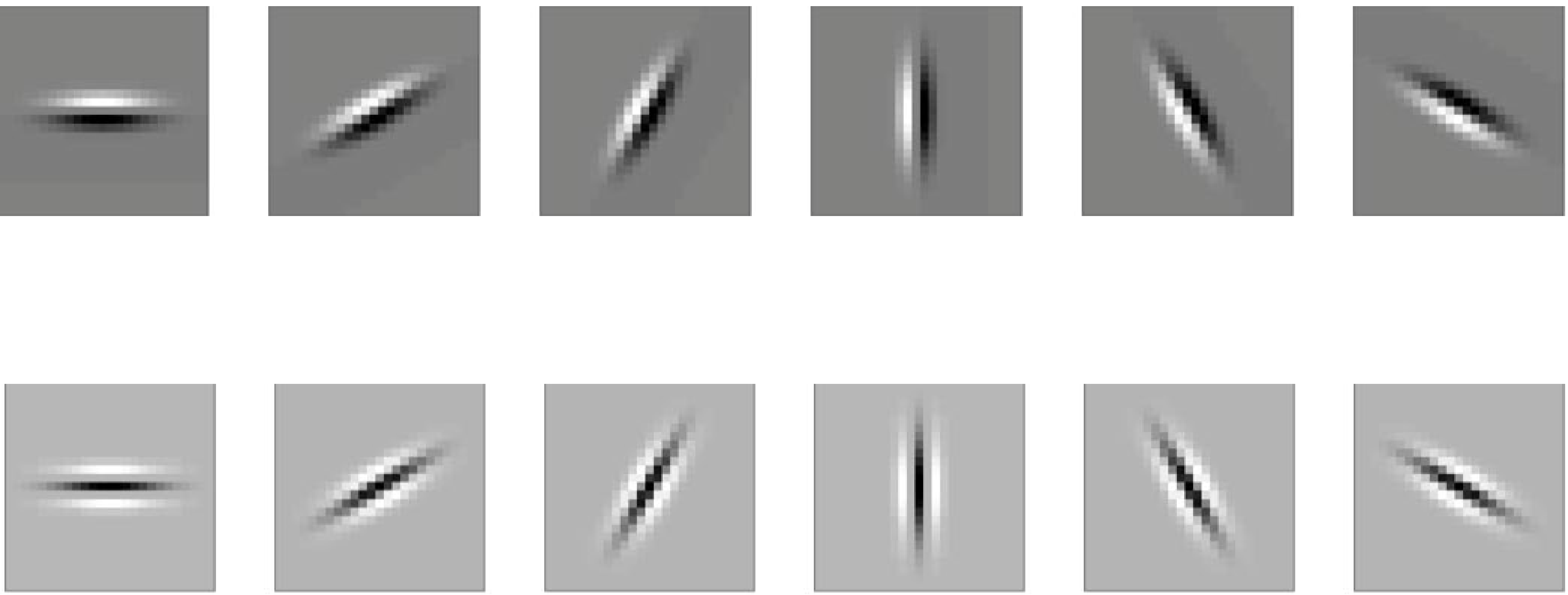
$$Rot_\theta f_1 = G'_{\sigma_1}(u)G_{\sigma_2}(v) \tag{10.6}$$
$$Rot_\theta f_2 = G''_{\sigma_1}(u)G_{\sigma_2}(v) \tag{10.7}$$

where we set

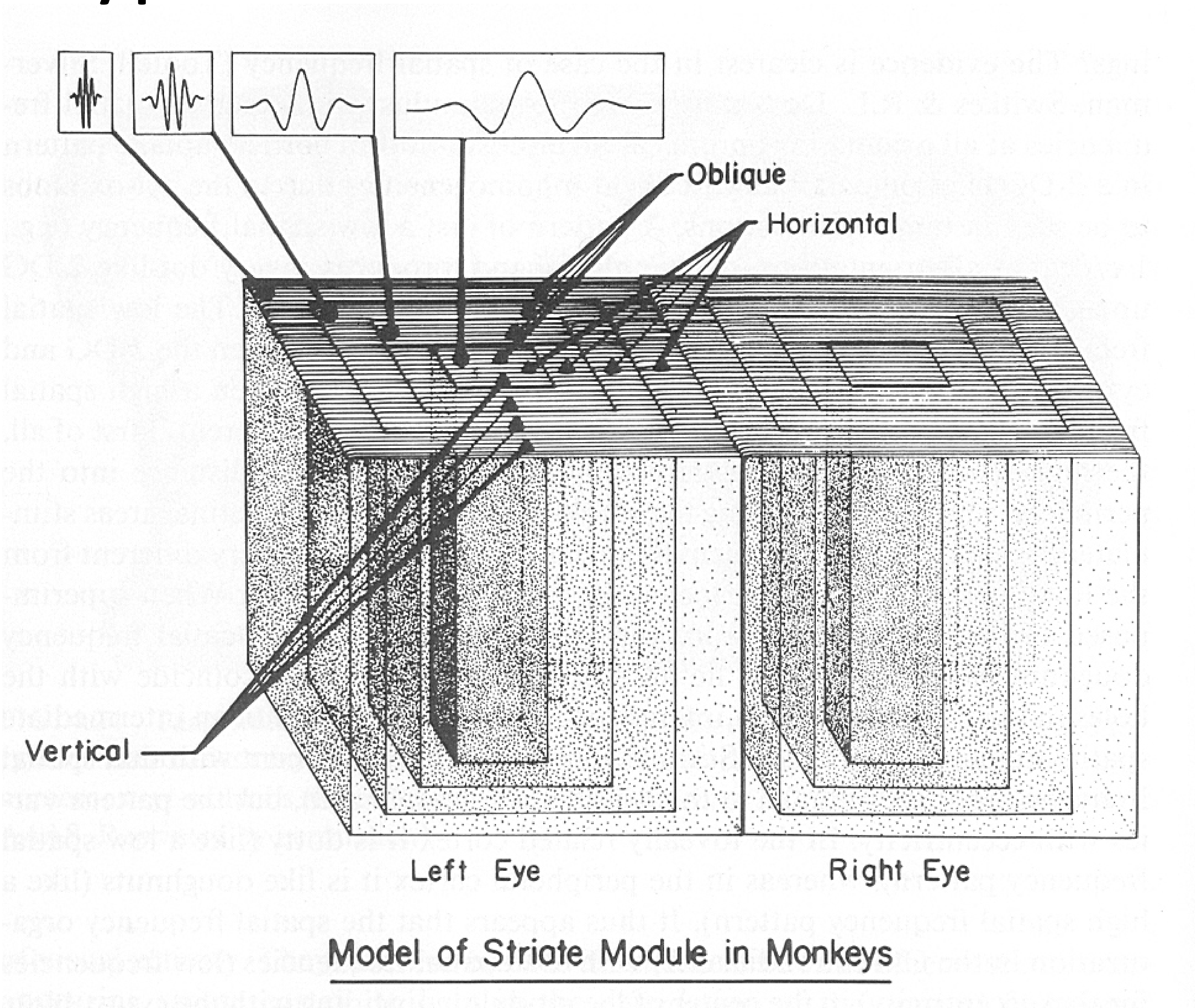
$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

These are useful when we convolve with 2D images, e.g. to detect edges at different orientations.

# Oriented Gaussian First and Second Derivatives

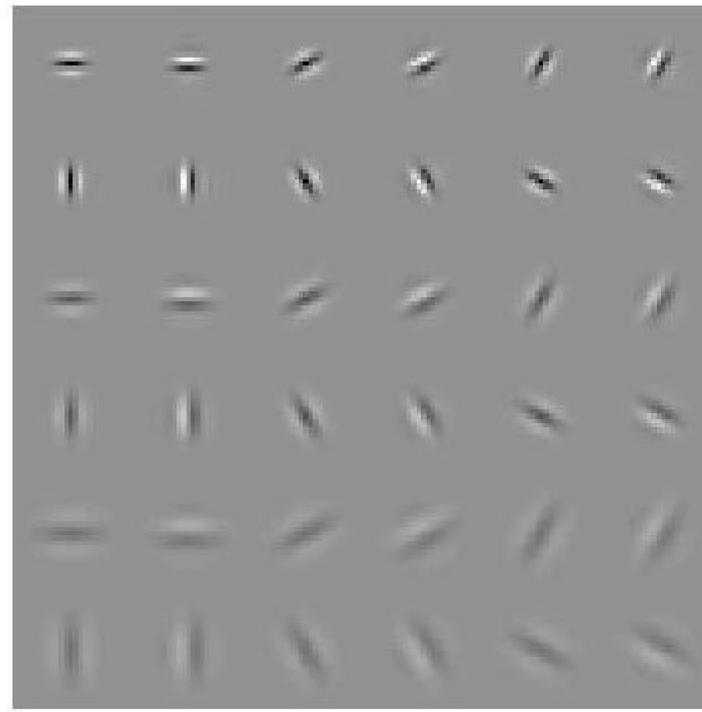


# Hypercolumns in visual cortex



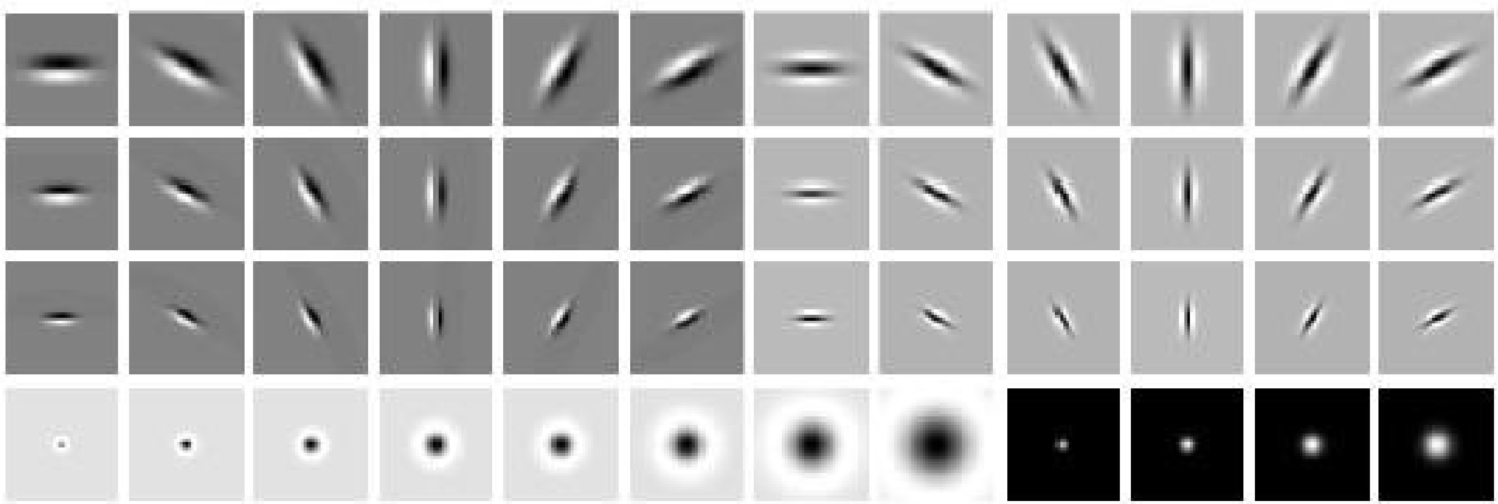
# Modeling hypercolumns

- Elongated directional Gaussian derivatives
- Gabor filters could be used instead
- Multiple orientations, scales



# Overcomplete representation: filter banks

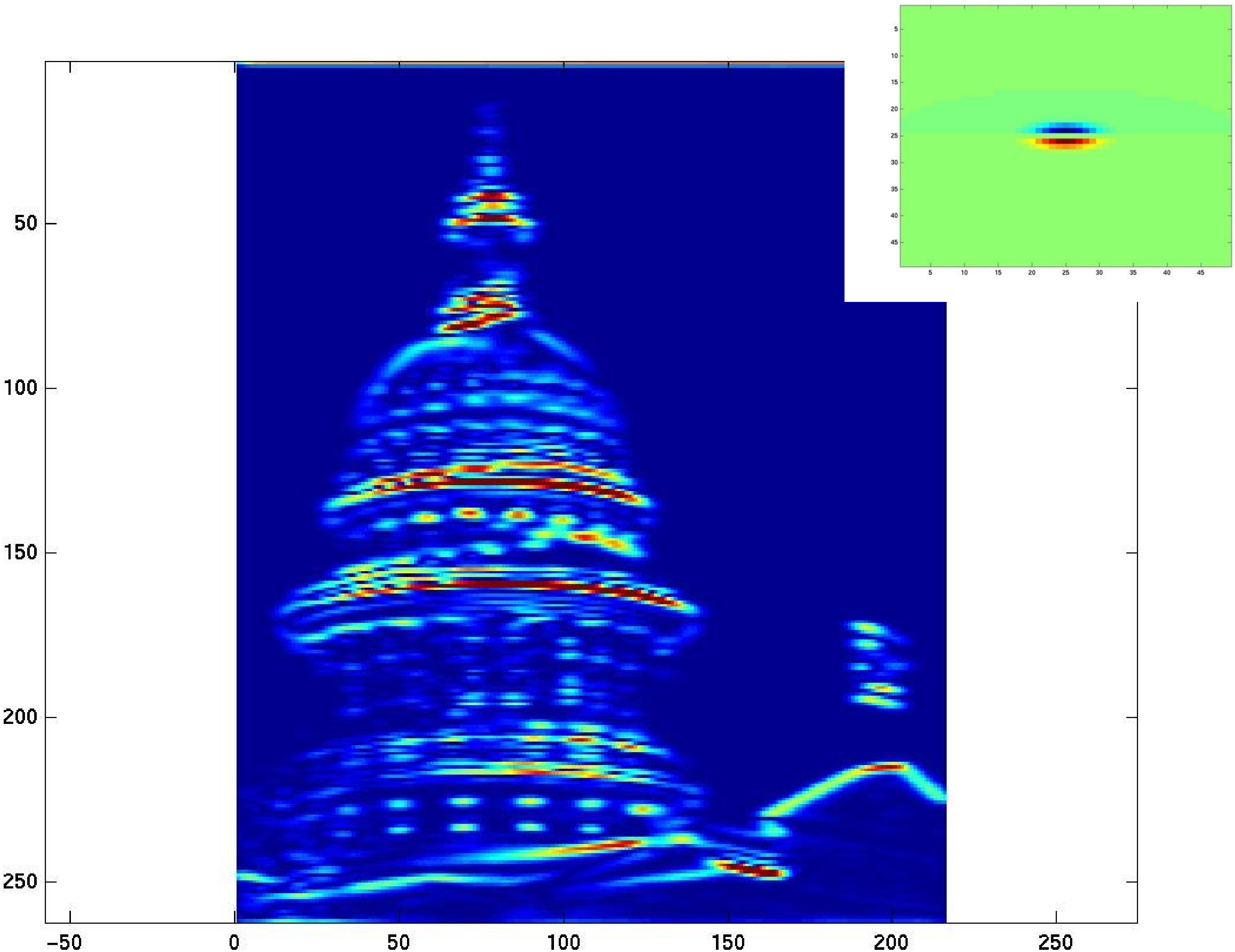
LM Filter Bank



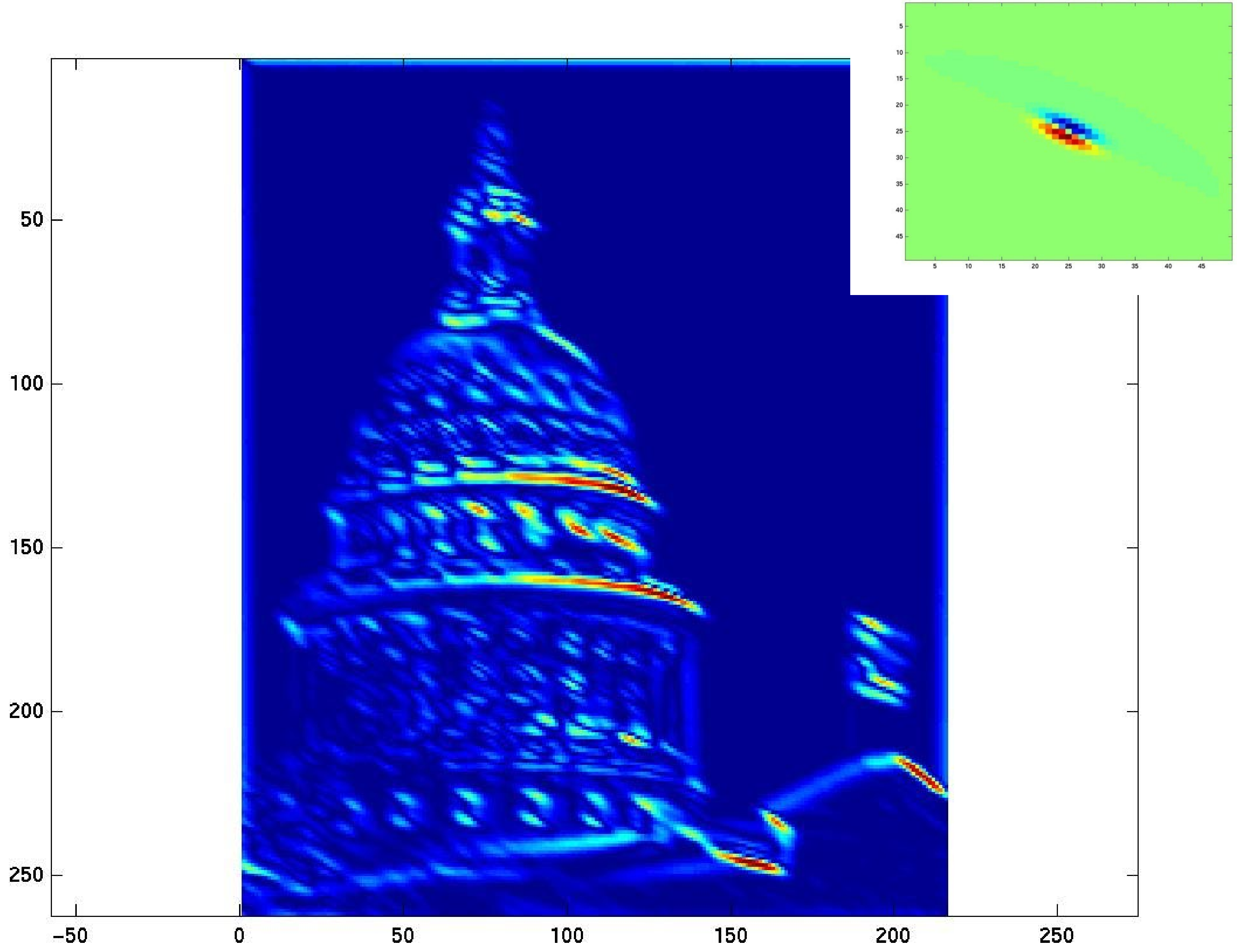
Code for filter banks: *www.robots.ox.ac.uk/~vgg/research/texclass/filters.html*

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

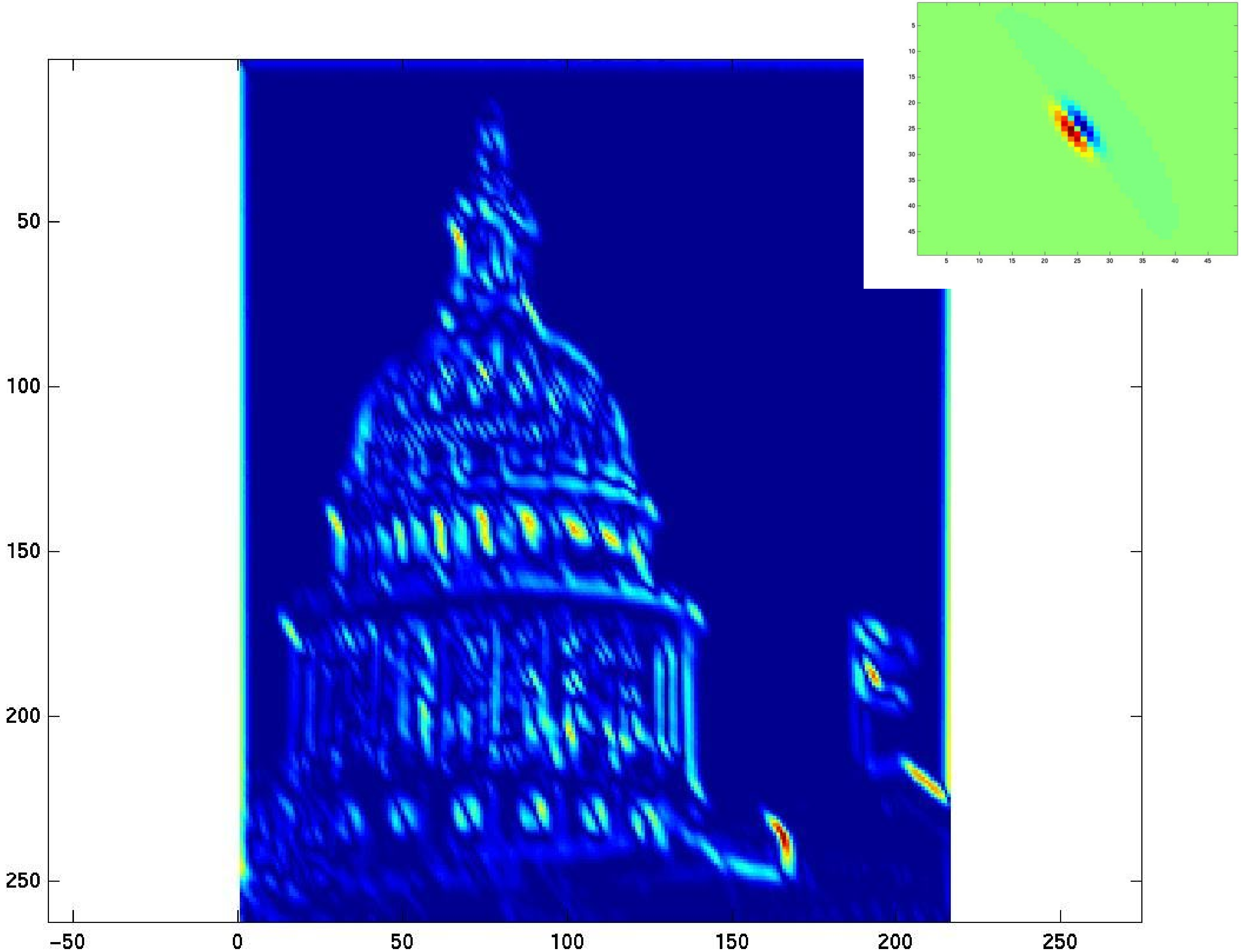
Kristen Grauman



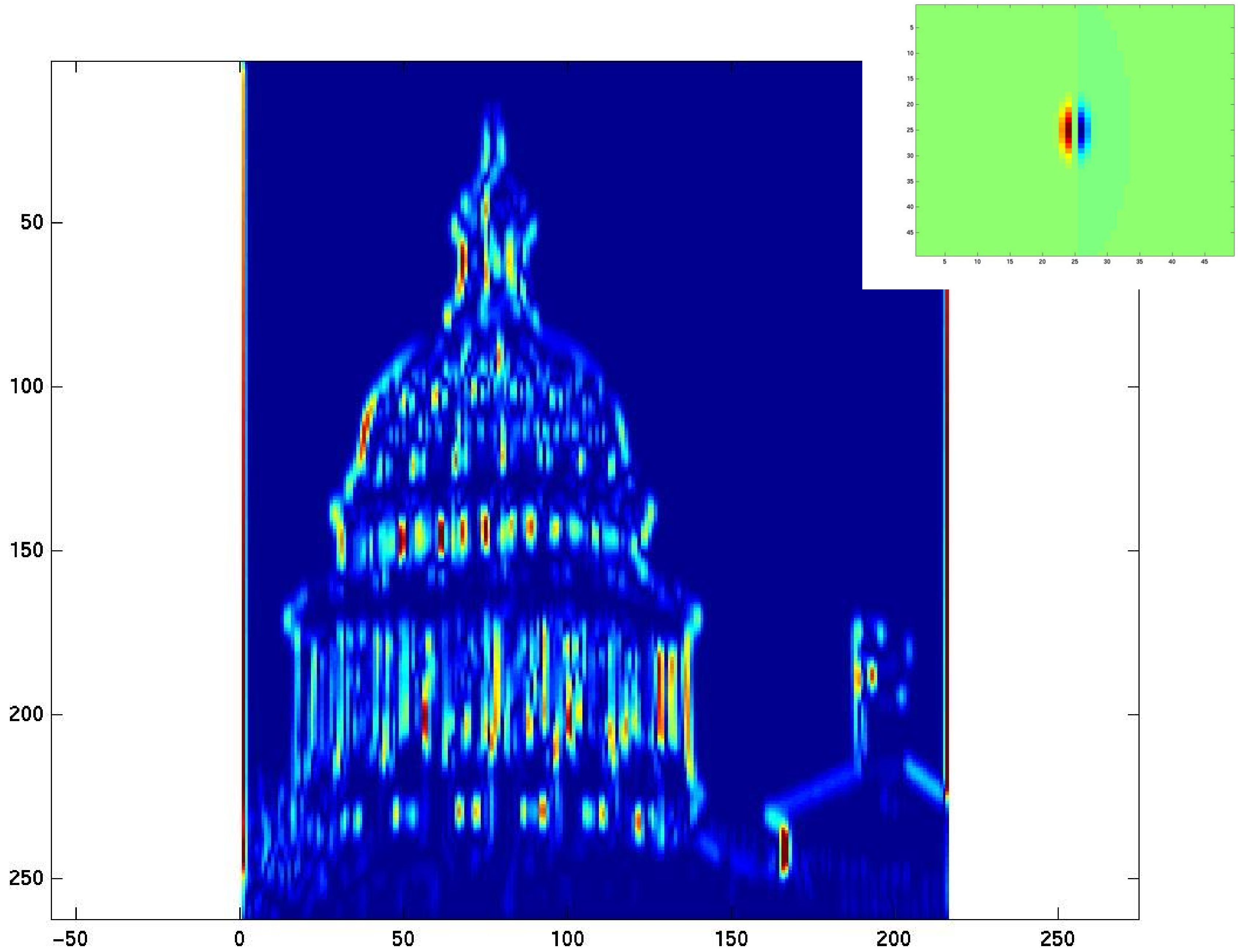

Kristen Grauman



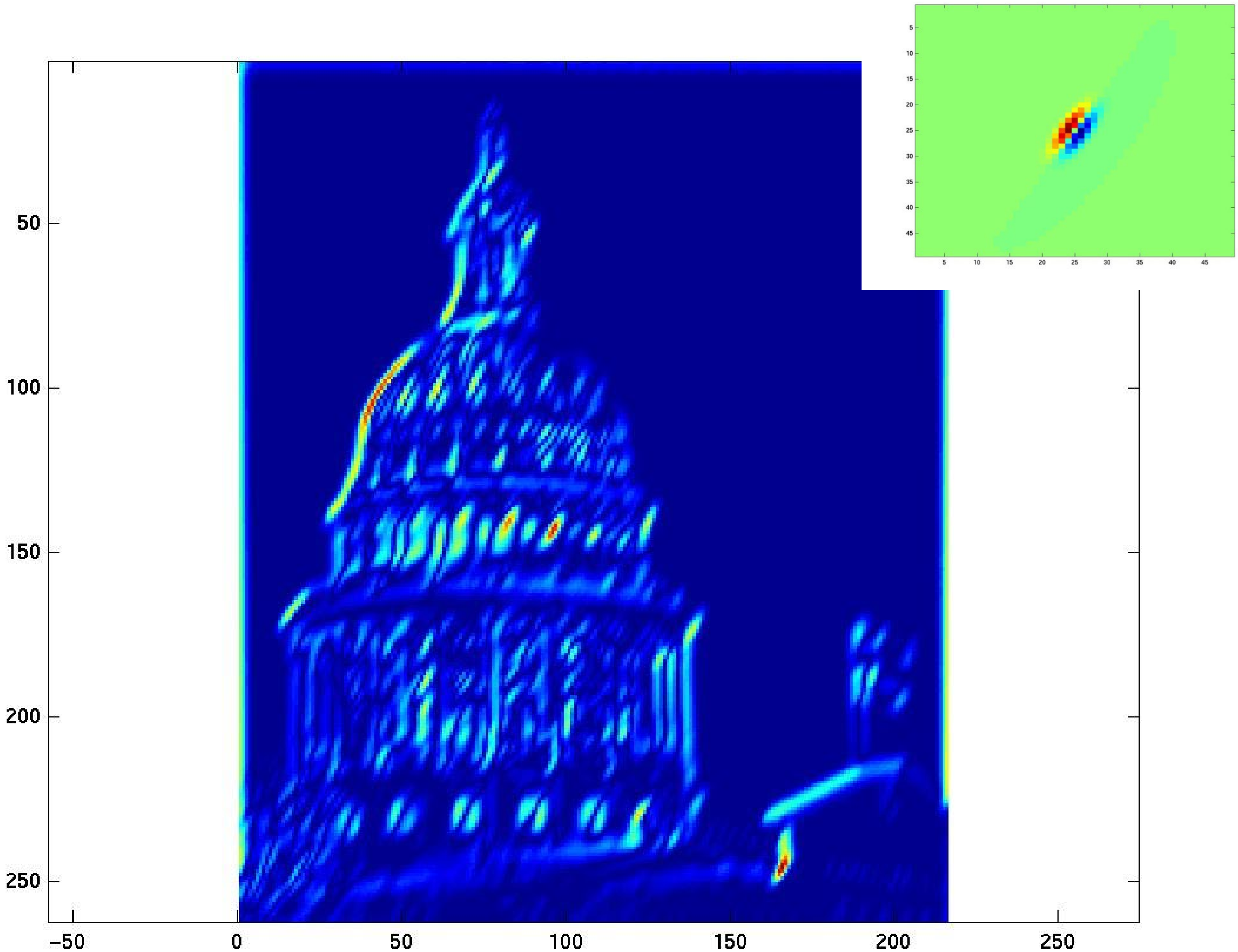

Kristen Grauman



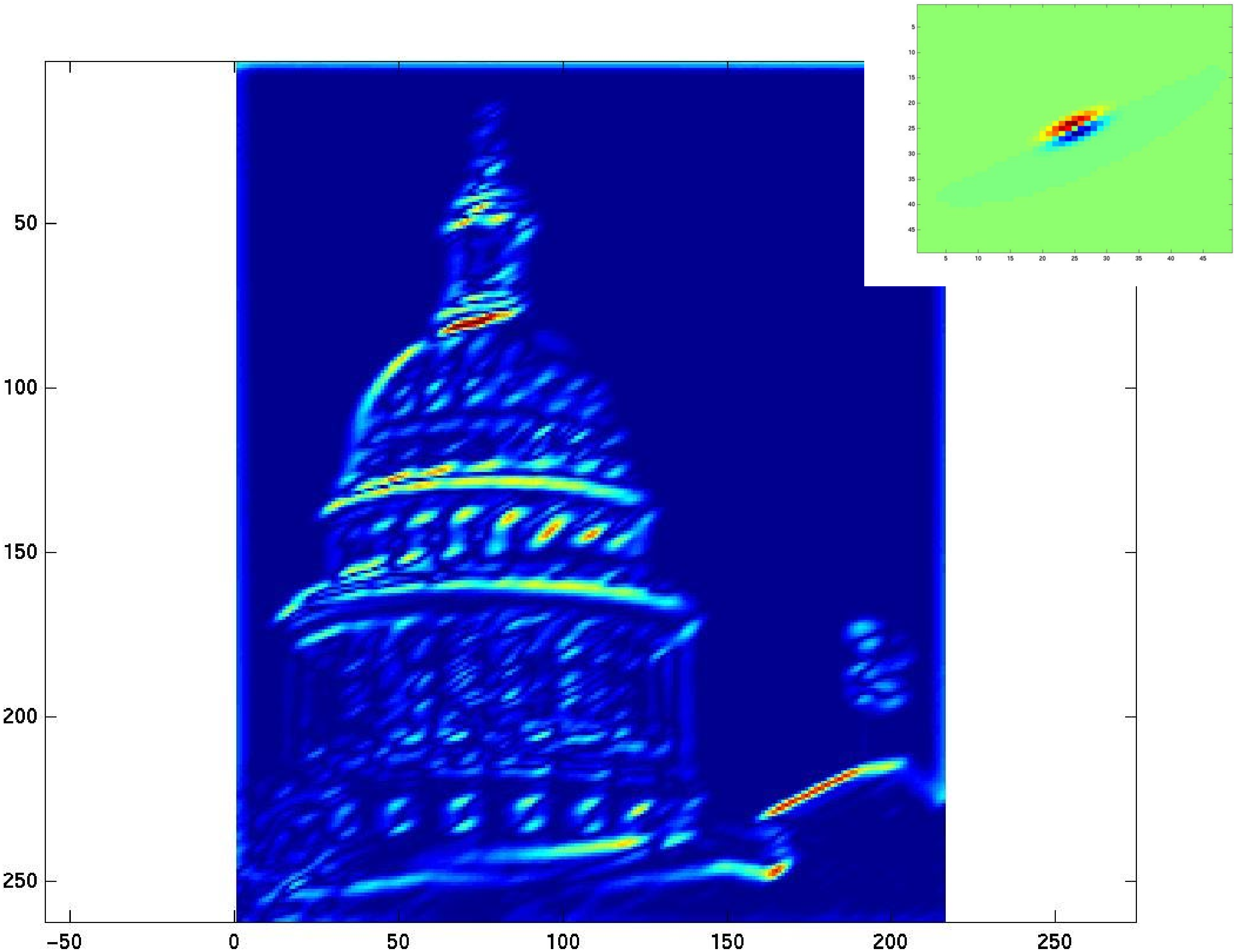

Kristen Grauman



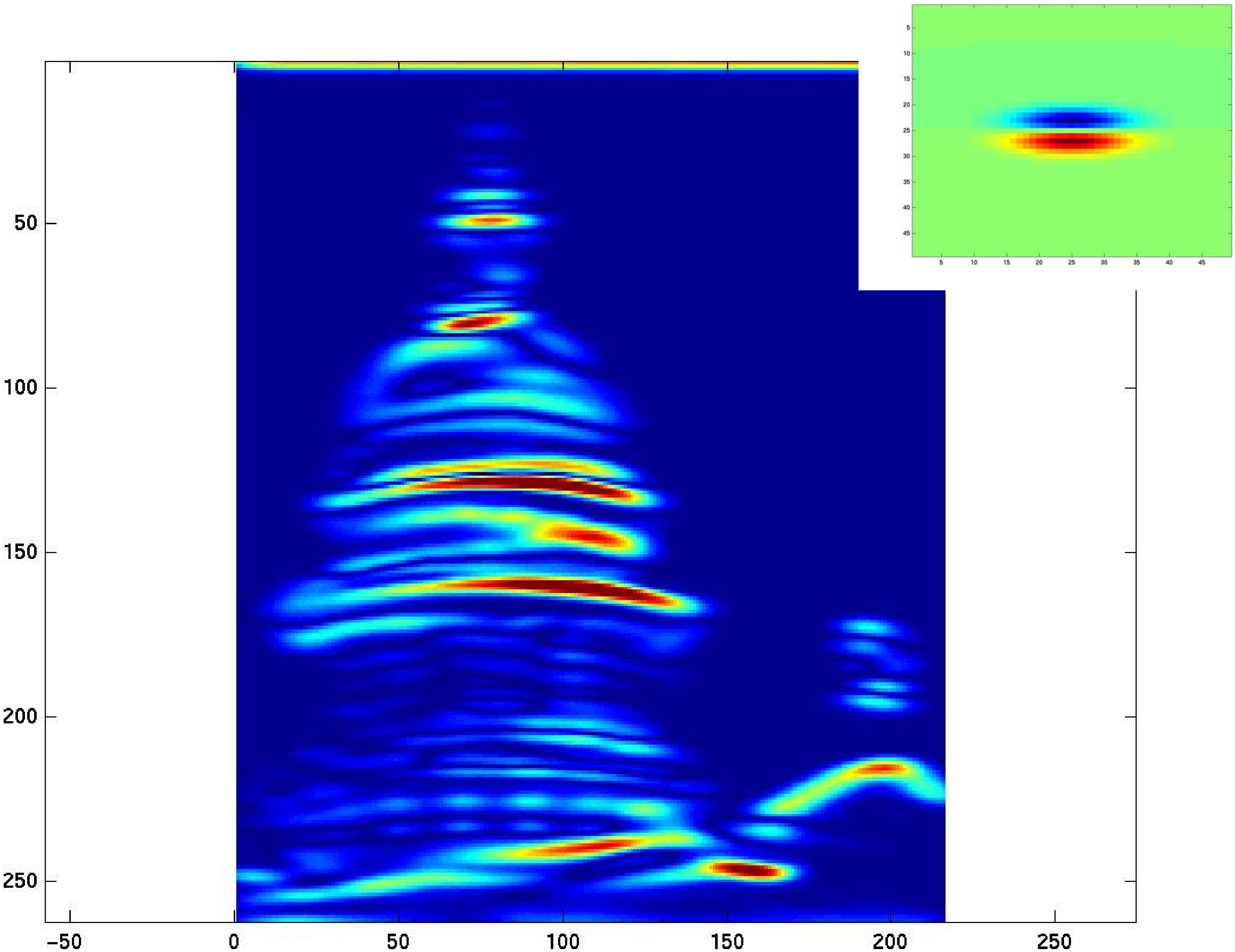

Kristen Grauman



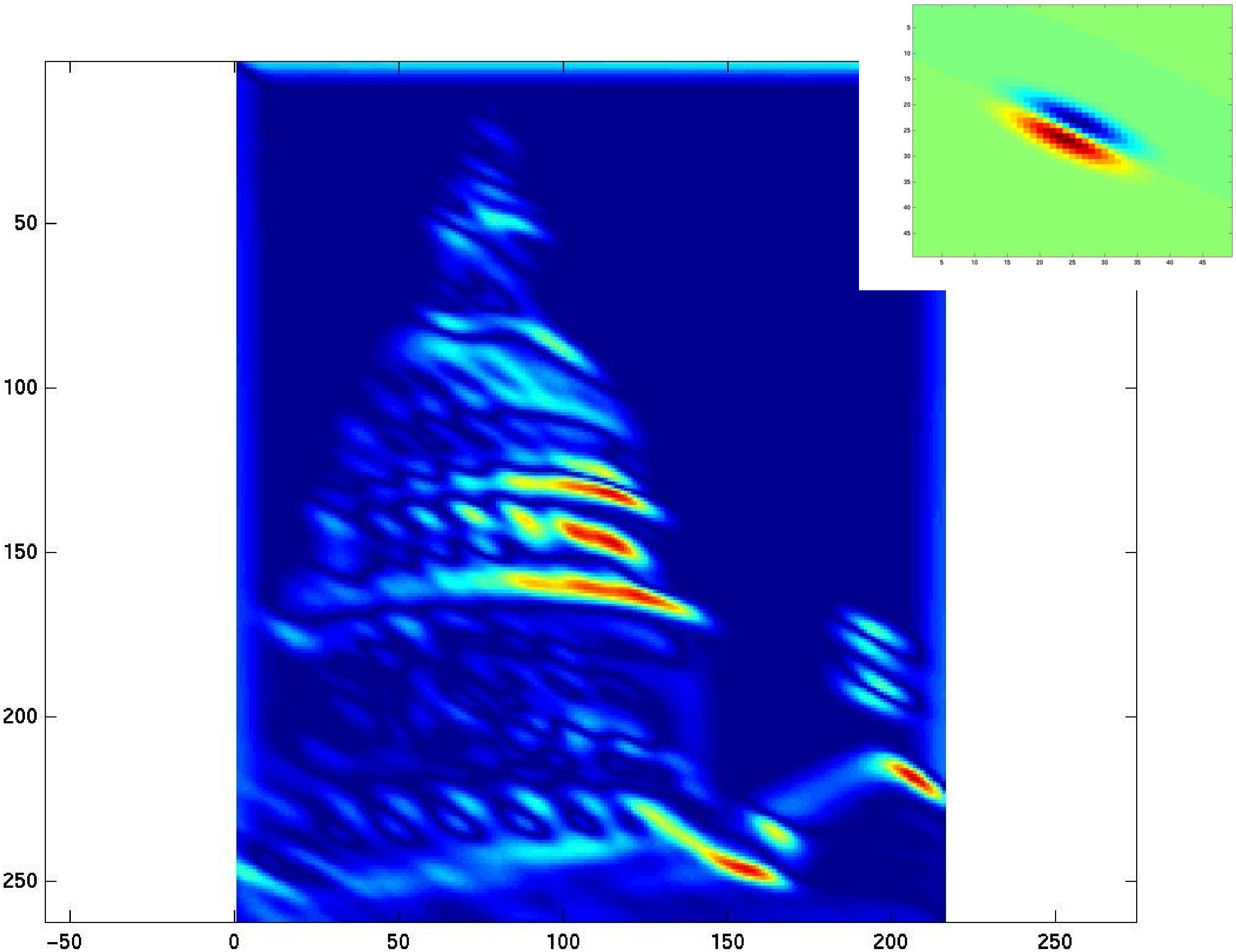

Kristen Grauman



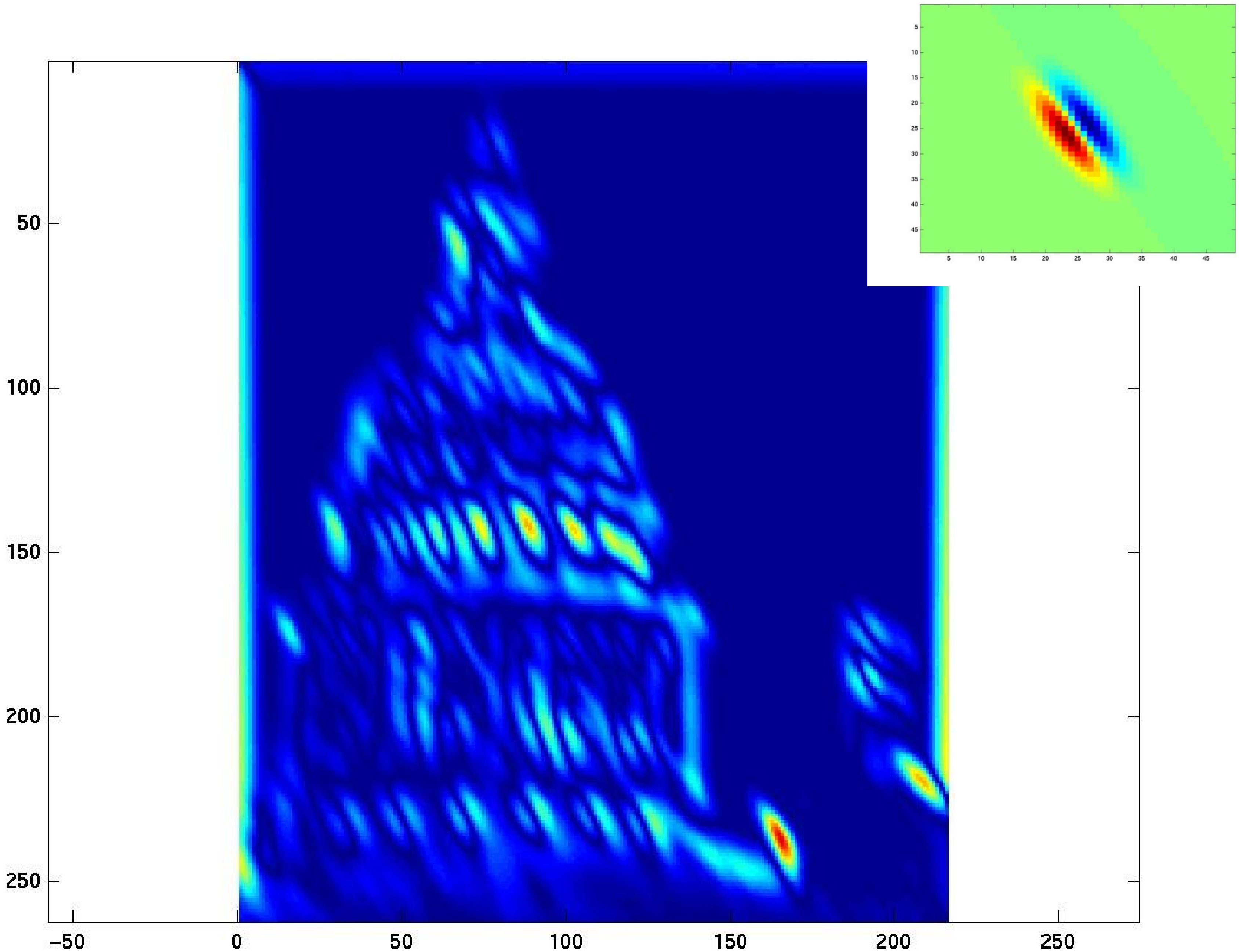

Kristen Grauman



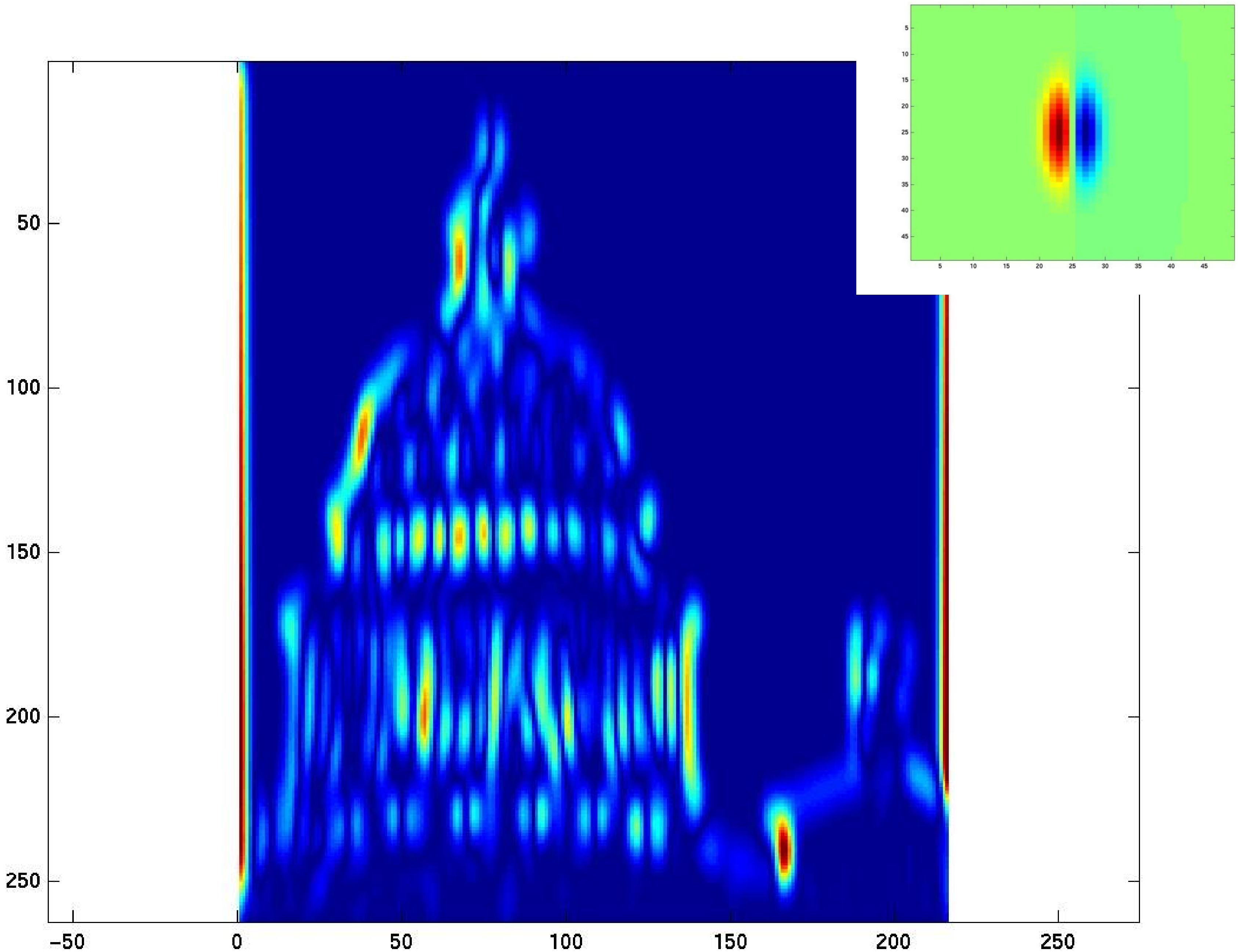

Kristen Grauman



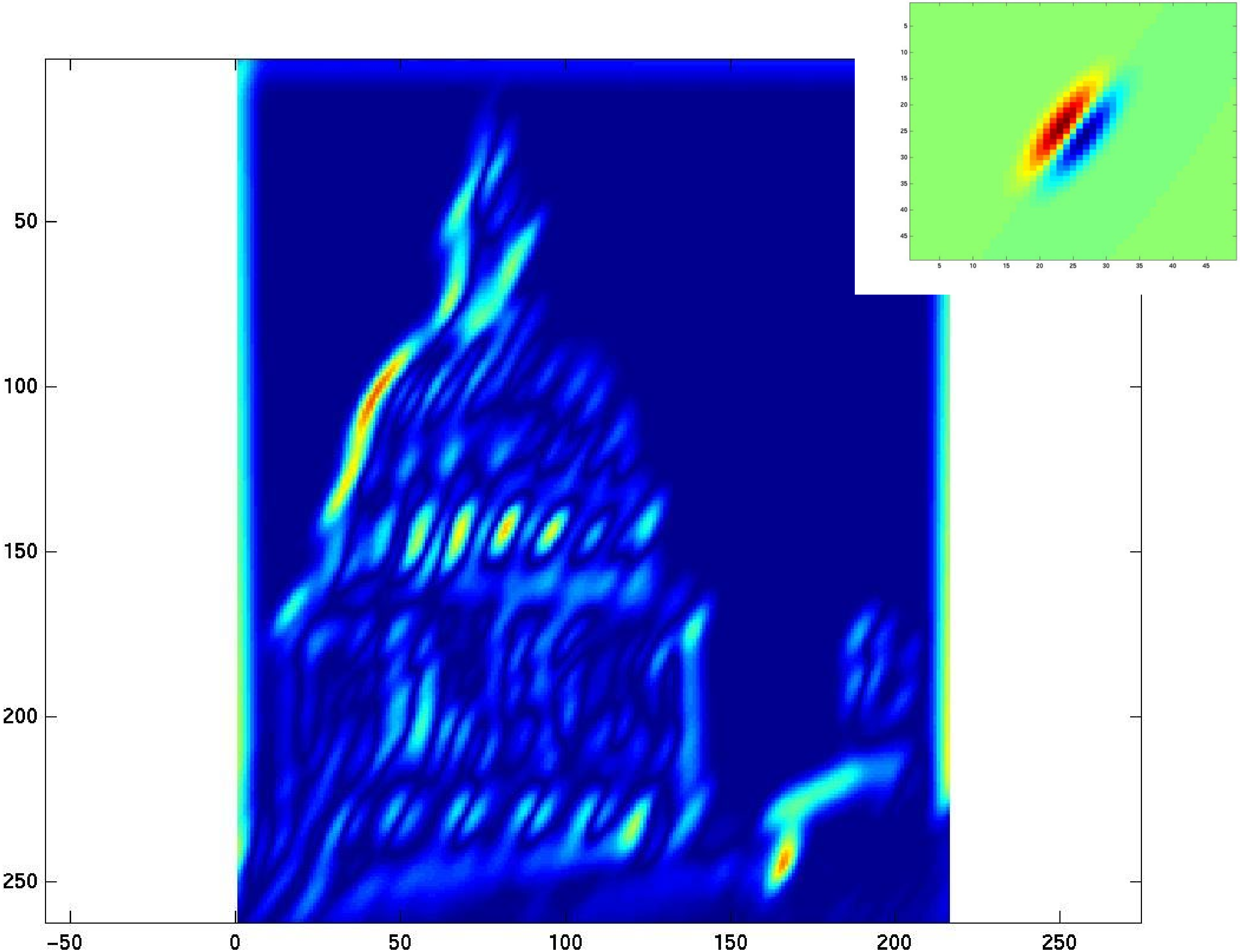

Kristen Grauman



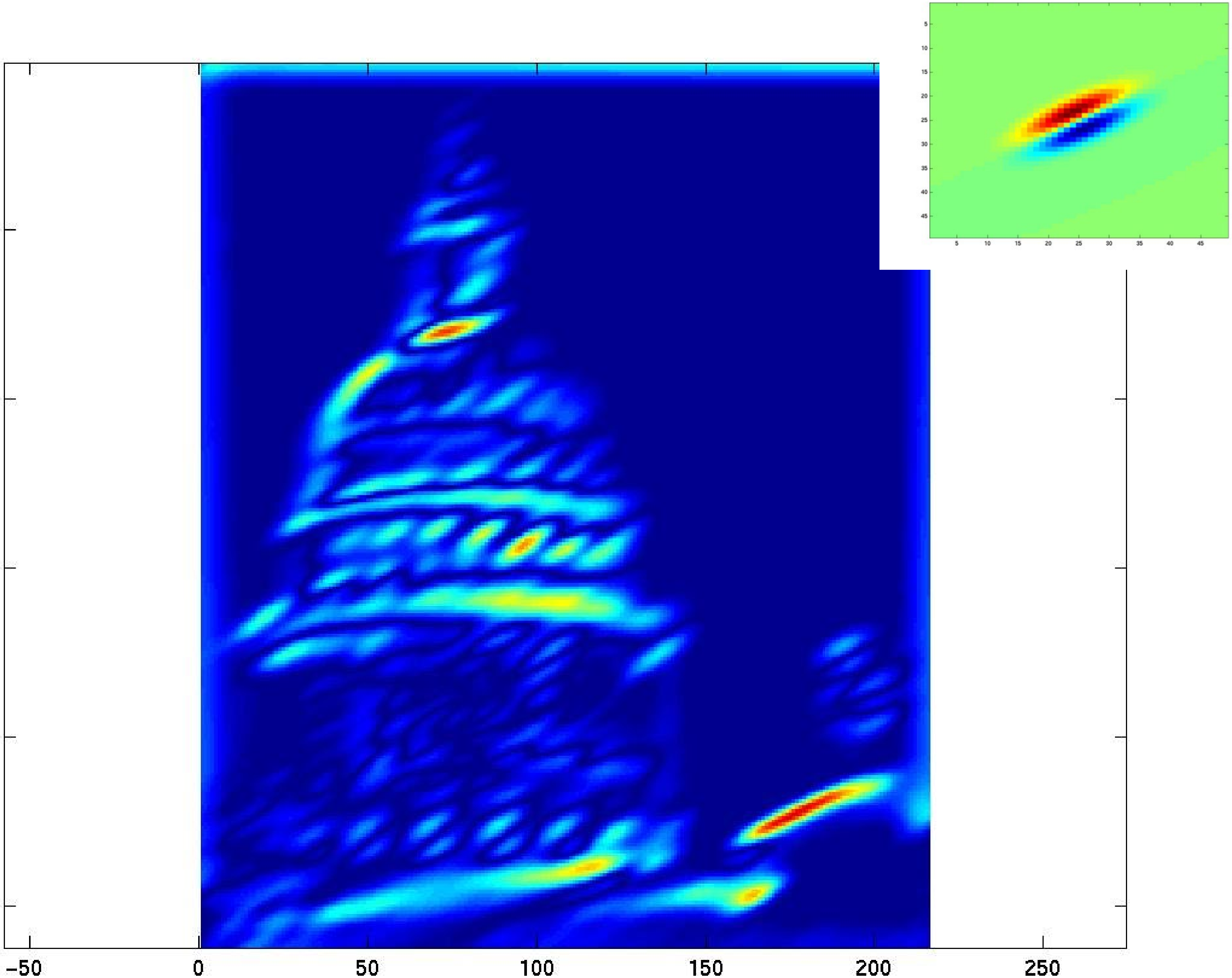

Kristen Grauman



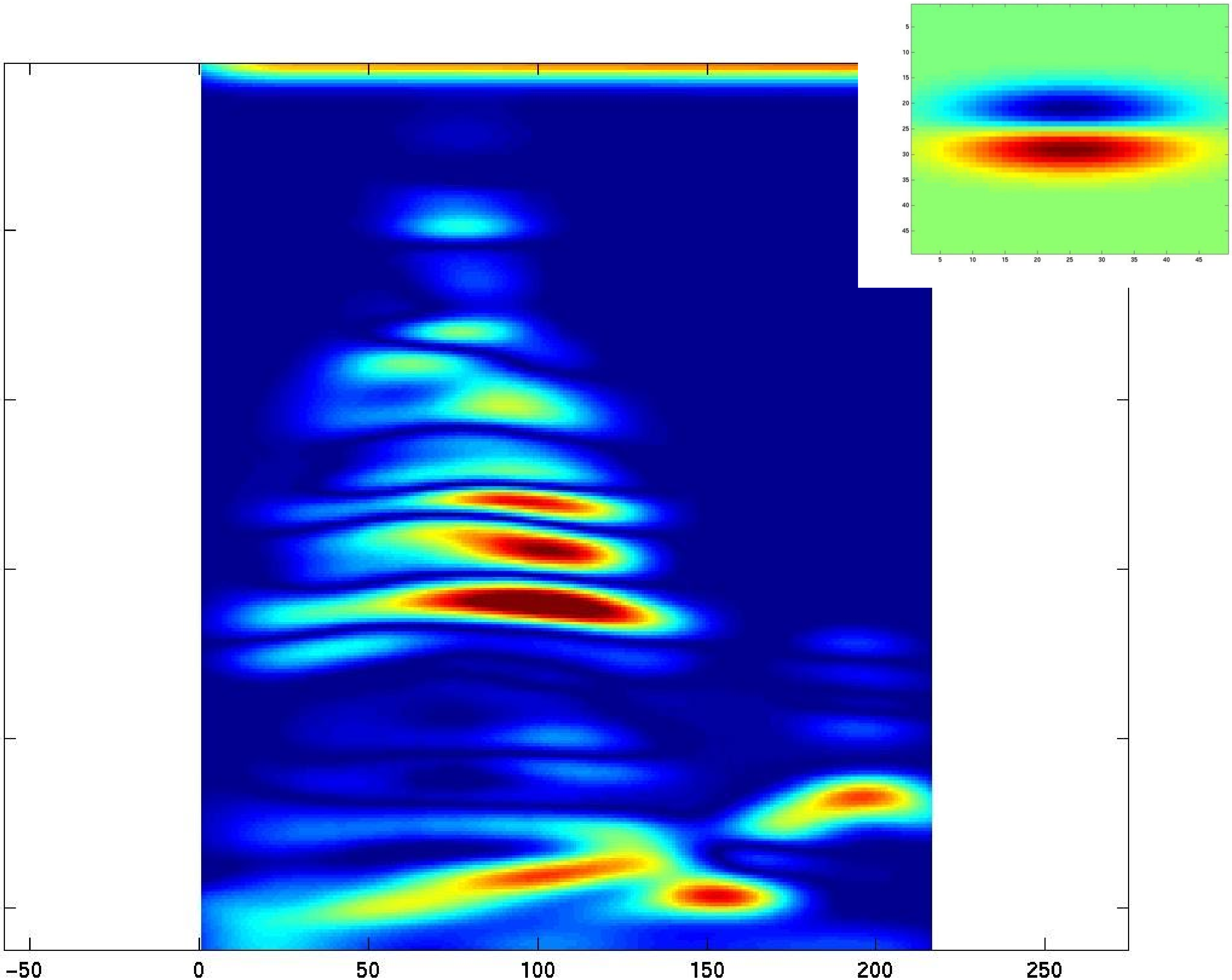

Kristen Grauman



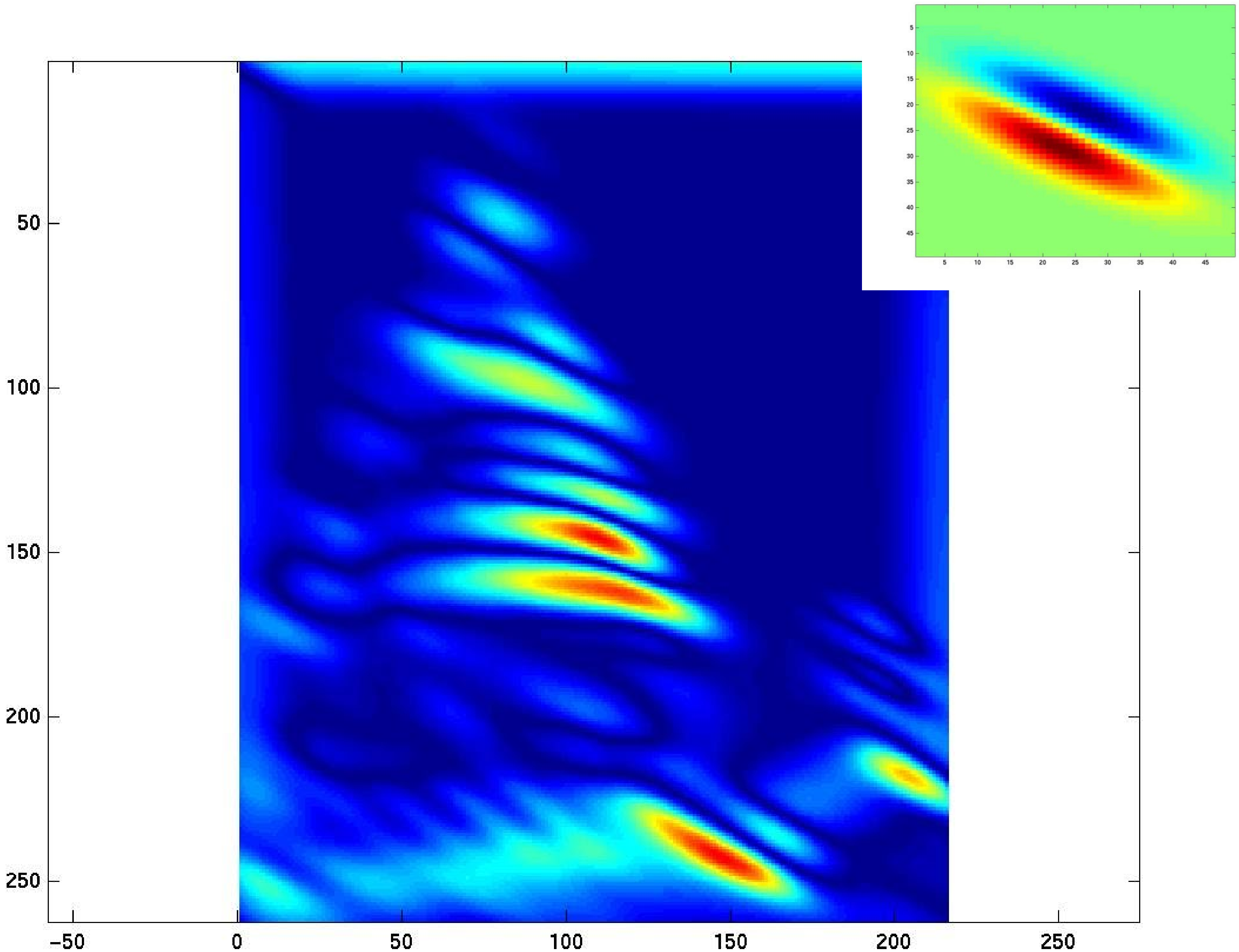

Kristen Grauman



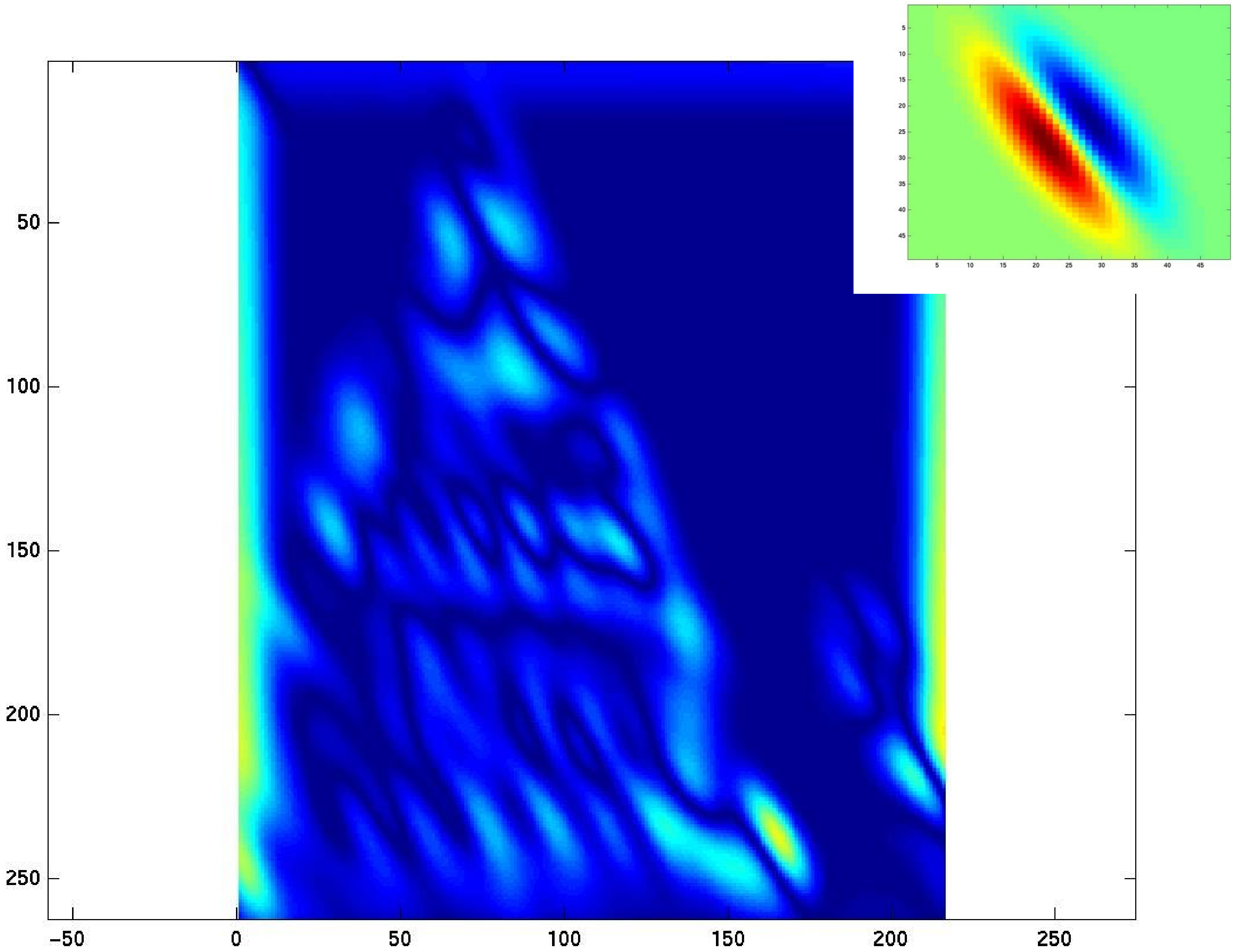

Kristen Grauman



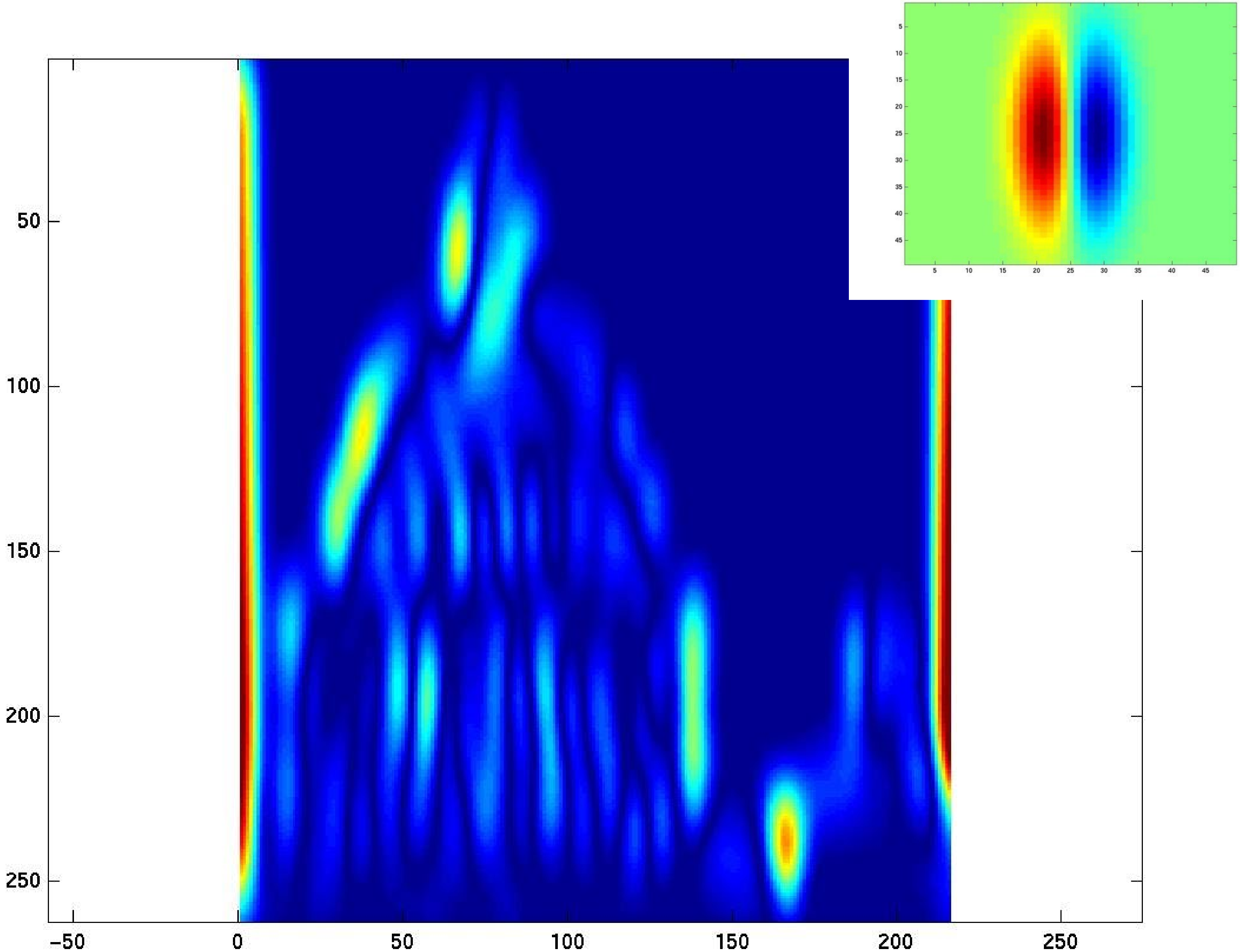

Kristen Grauman



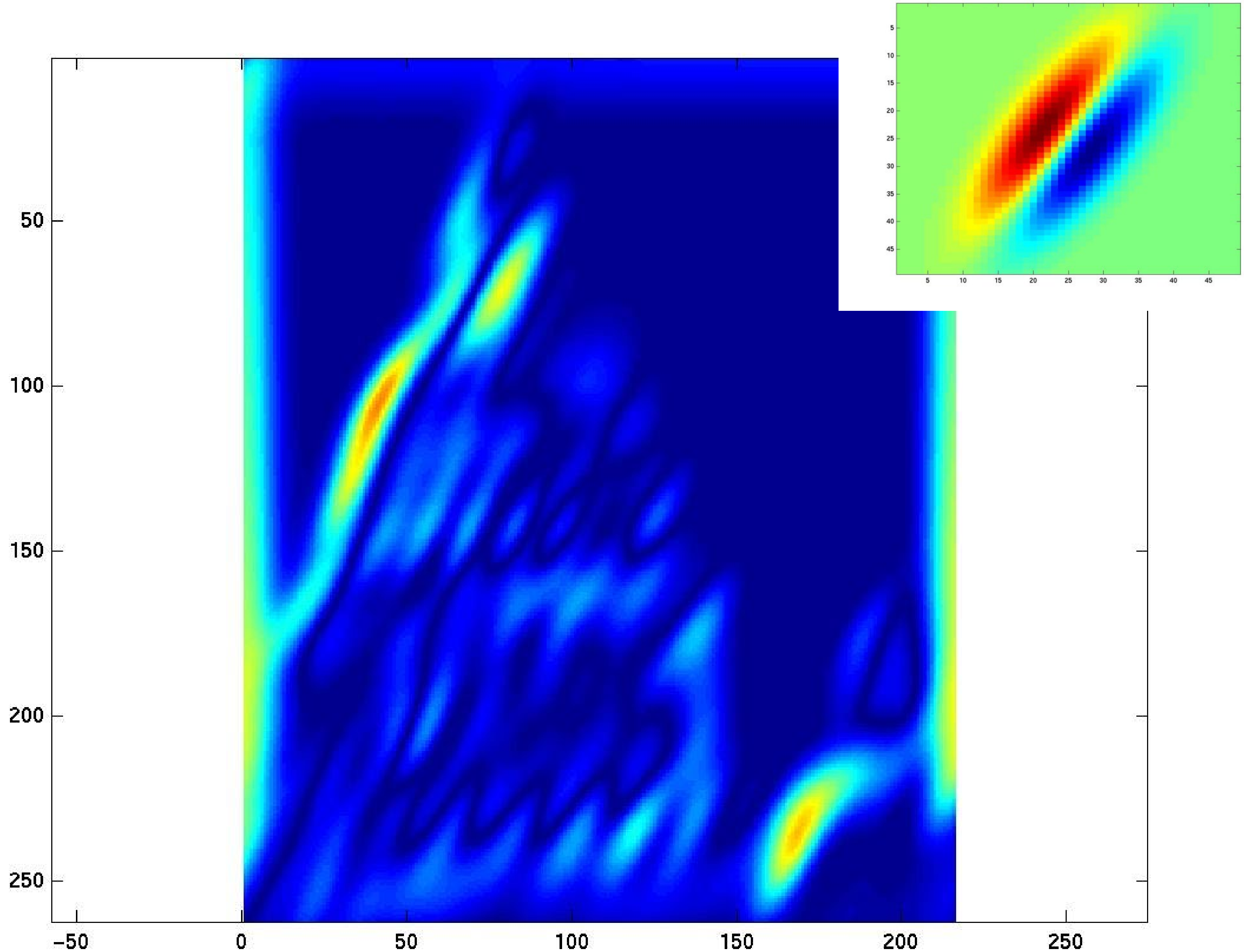

Kristen Grauman



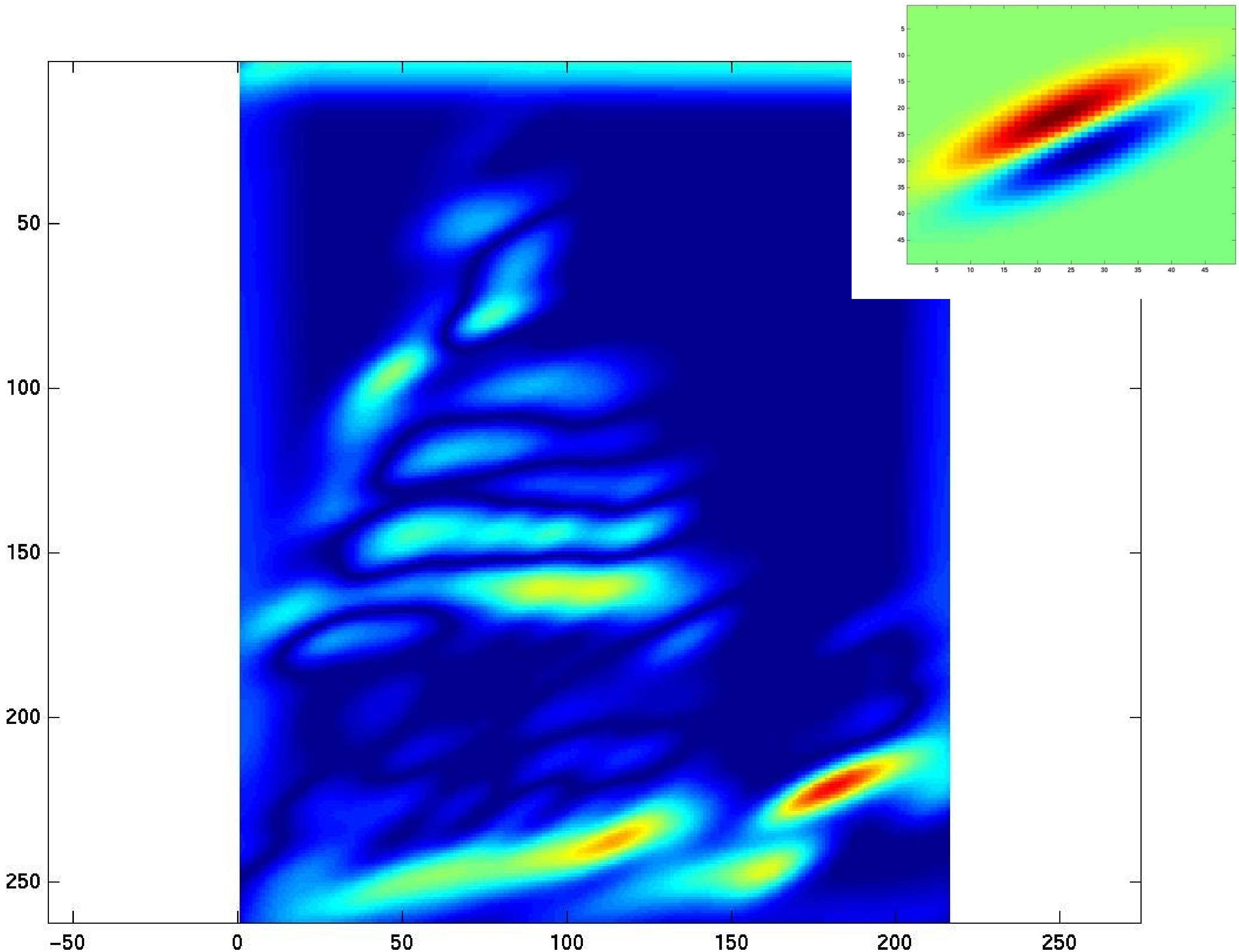

Kristen Grauman



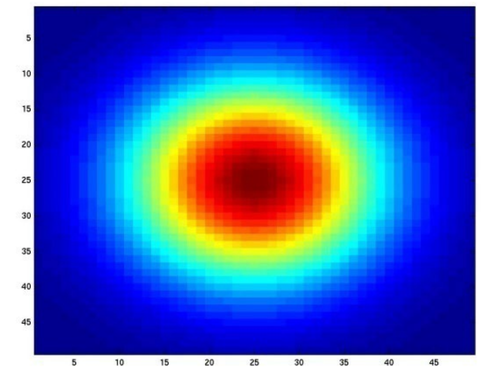

Kristen Grauman




Kristen Grauman




Kristen Grauman

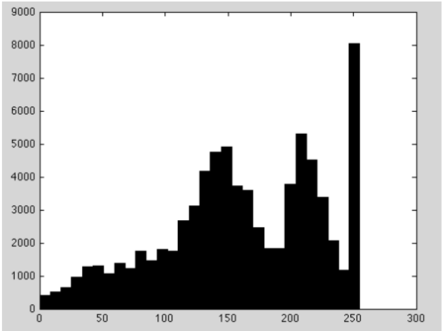

Kristen Grauman

# Two questions of texture modeling

- What are the texture features (textons)?
  - Pixels
  - Pixel patches
  - Outputs of V1-like filters
  - Clusters of patches / filter outputs
  - CNN features
  - Etc.

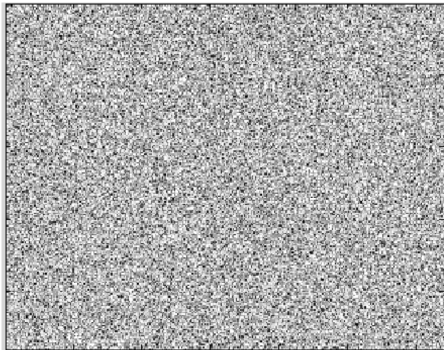
- How do we aggregate statistics
  - Various types of histograms
  - Implicit or explicit

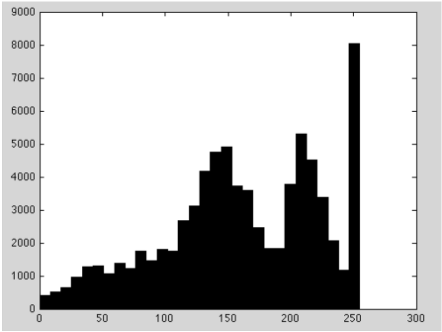
# Pixel Histograms

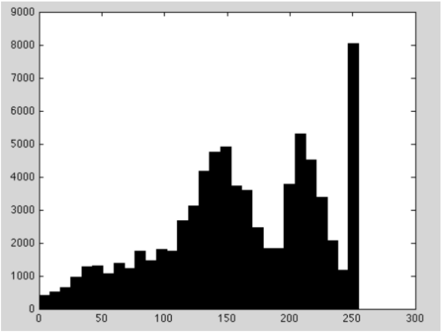



Slide by Erik Learned-Miller

# Pixel Histograms

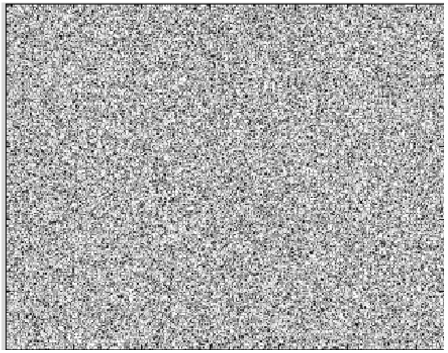





Slide by Erik Learned-Miller

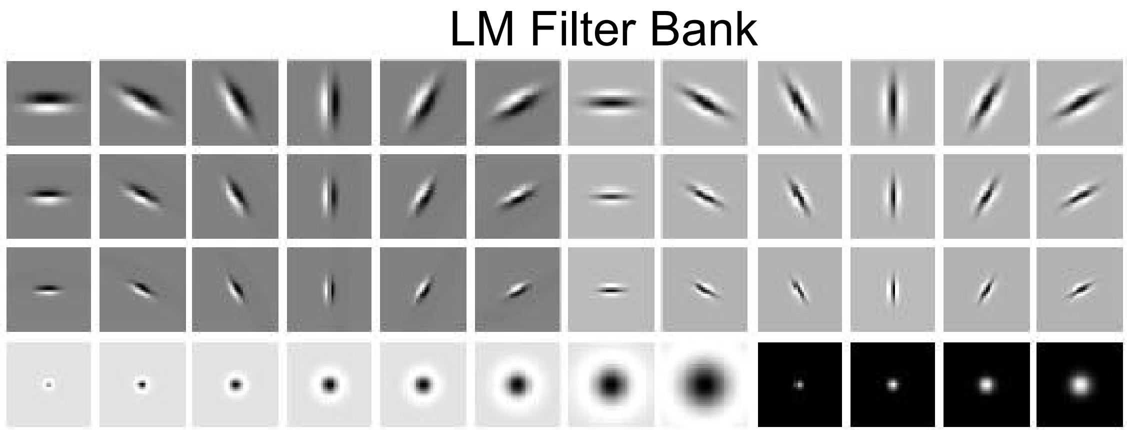
# Gray value histogram comparisons



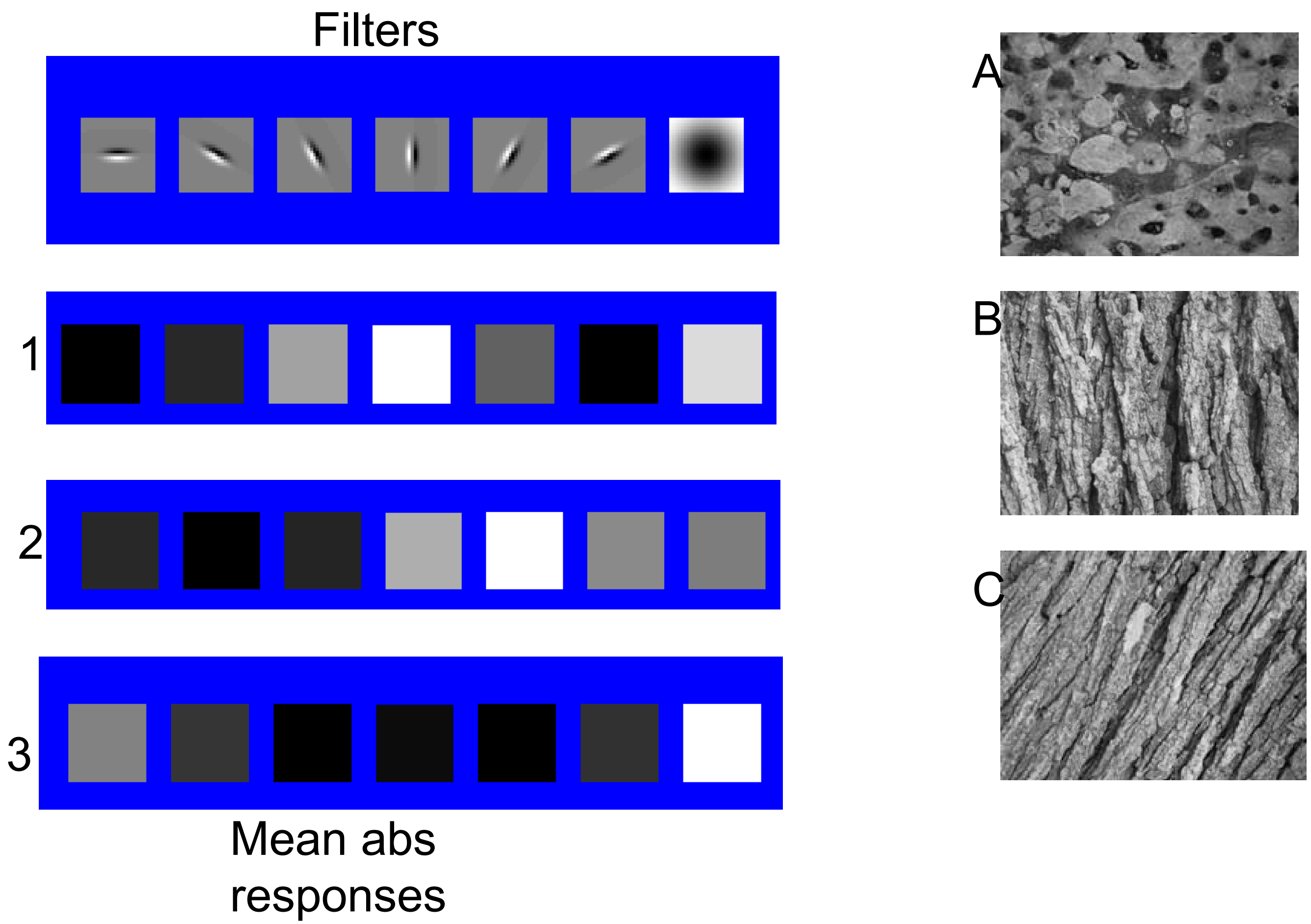
They're equal

Slide by Erik Learned-Miller

# Going up from pixels: V1 filter-banks

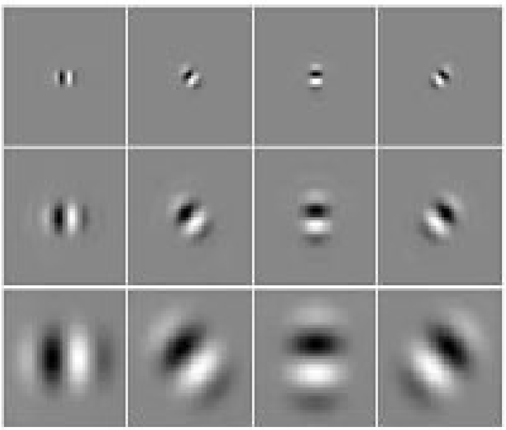


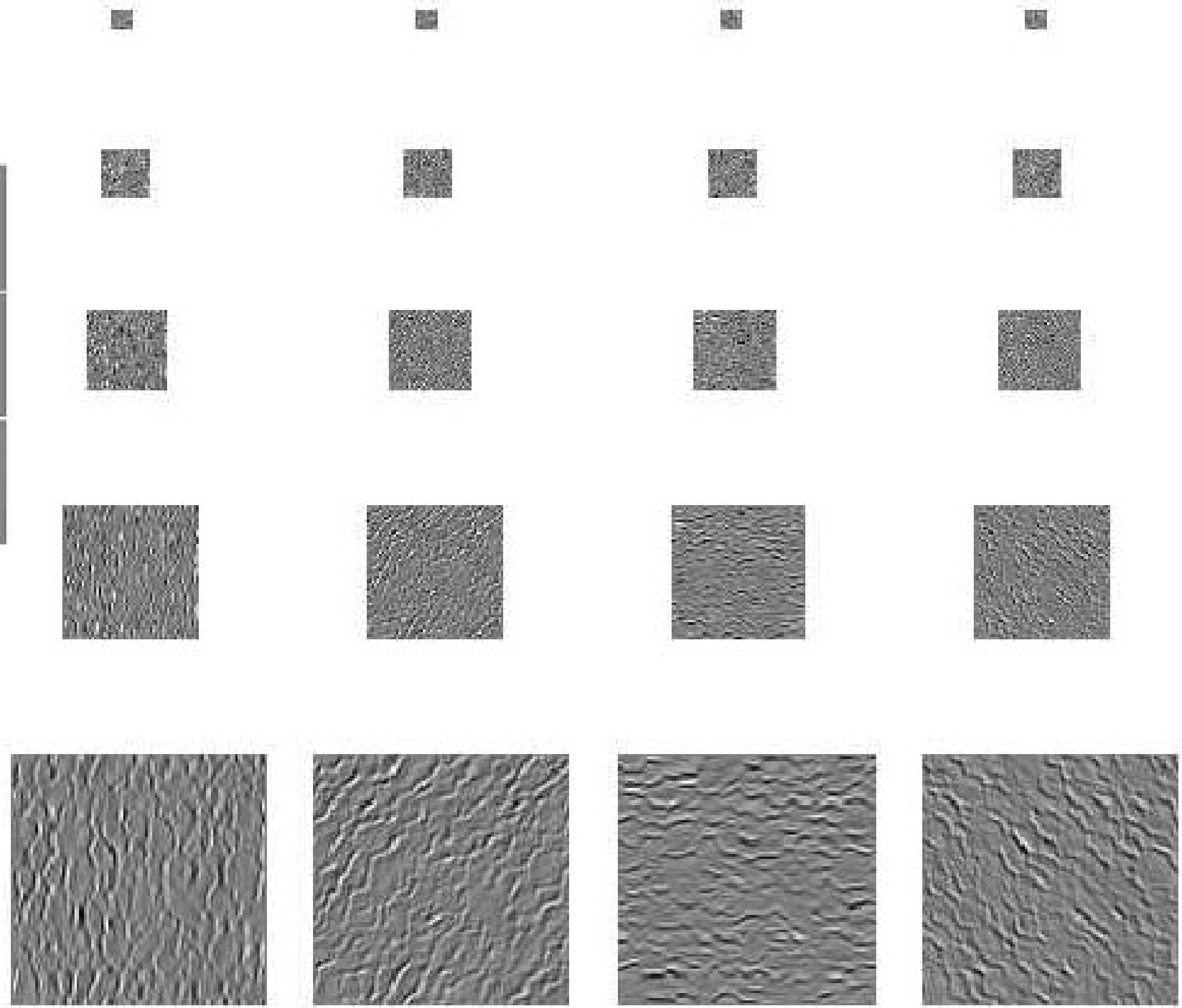
# Can you match the texture to its histogram?



# Slightly fancier: histogram for each filter

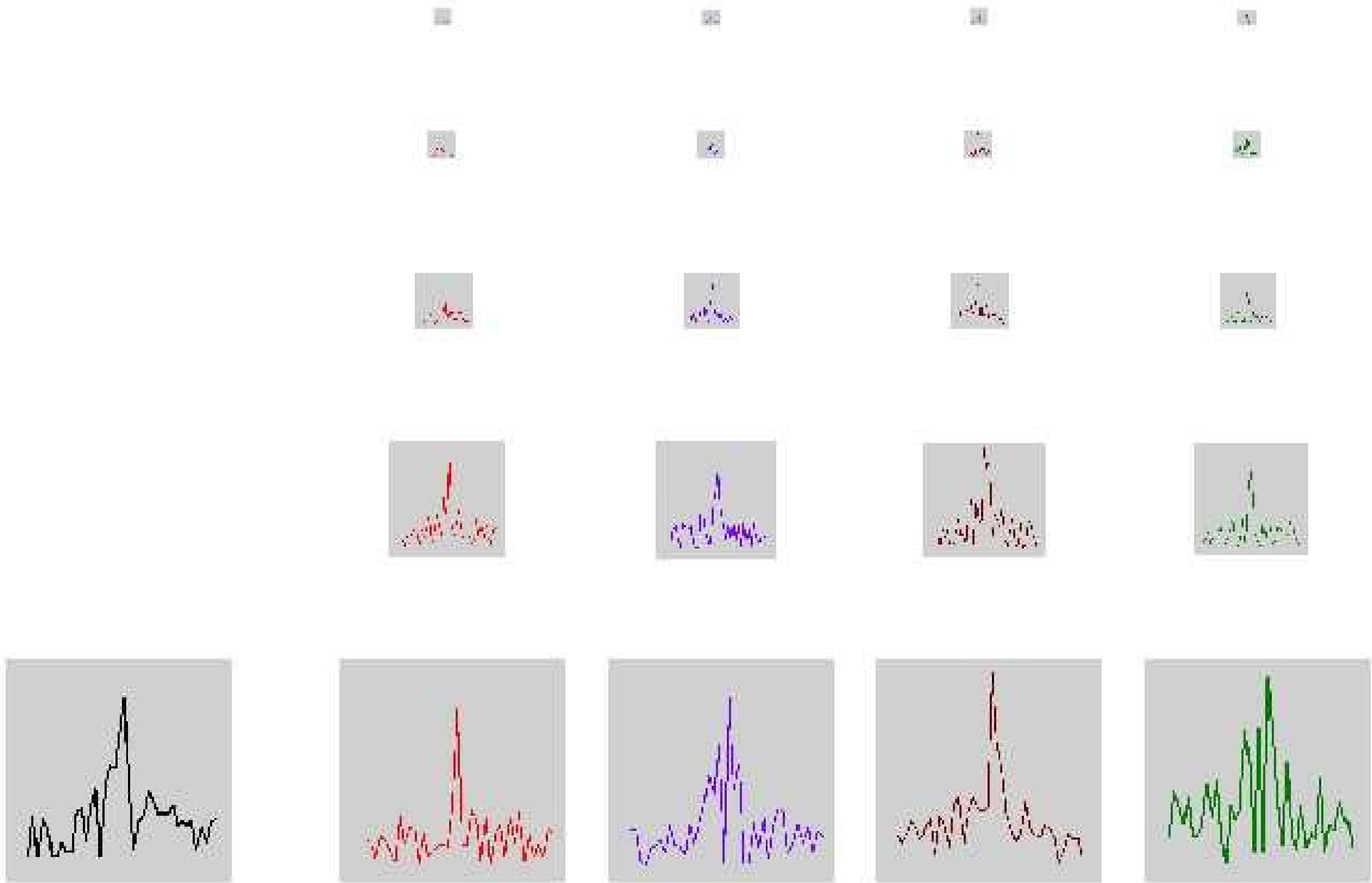
Filter bank



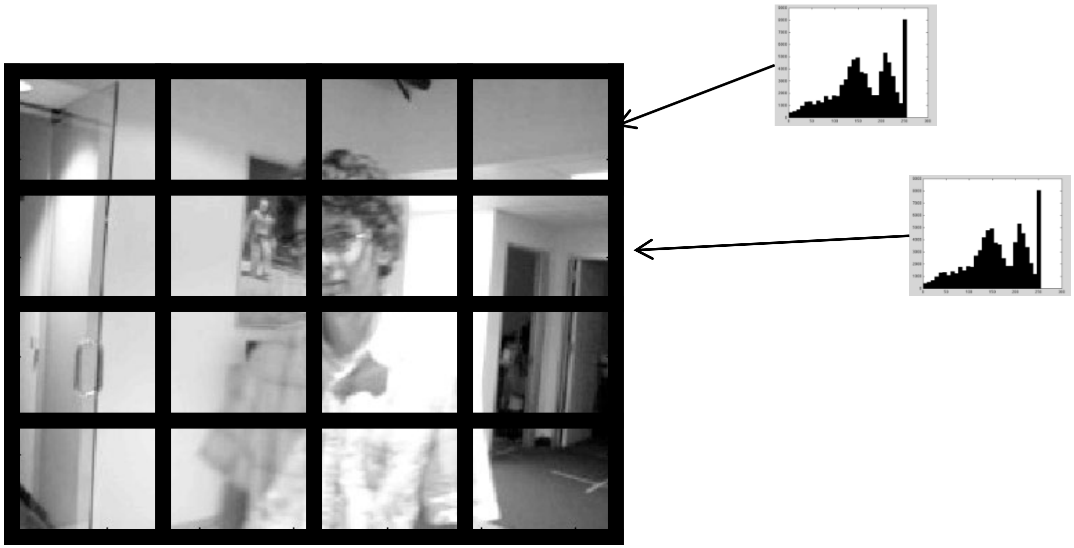


Input image

# Filter response histograms



# Adding spatial structure

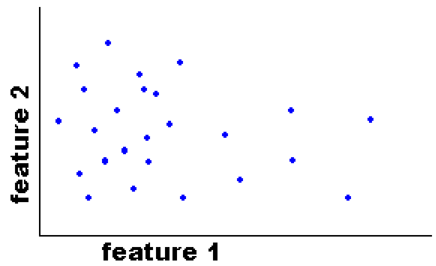


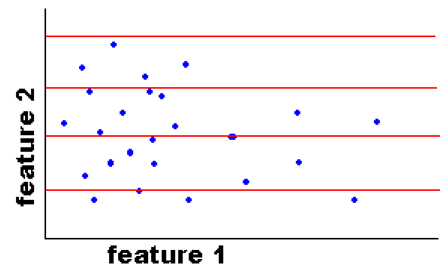
A separate histogram for each region.

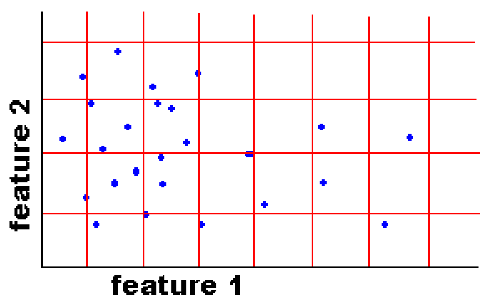
Slide by Erik Learned-Miller

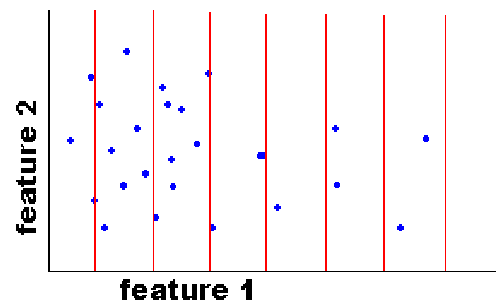
# Image Representations: Histograms

Images from Dave




Joint histogram

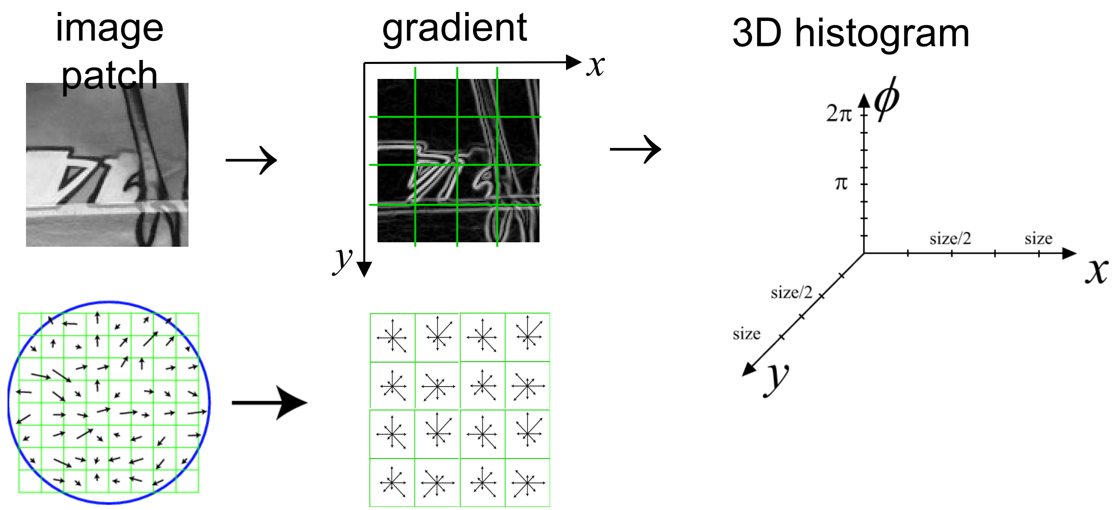
- Requires lots of data
- Loss of resolution to avoid empty bins

Marginal histogram

- Requires independent features
- More data/bin than joint histogram

# Ex: SIFT descriptor [Lowe'99]

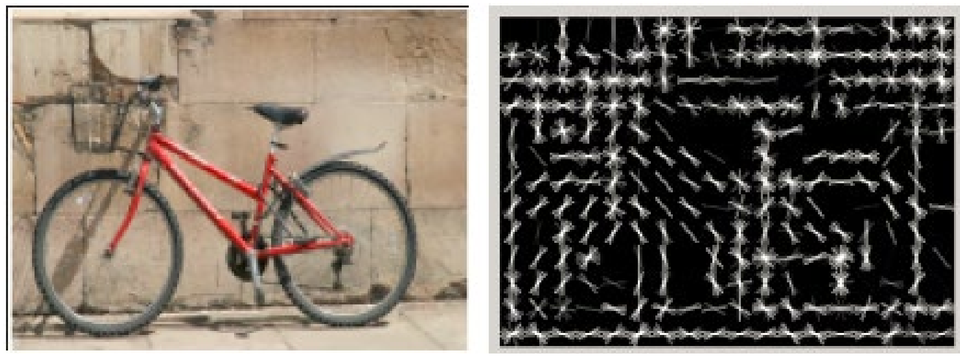
distribution of the gradient over an image patch



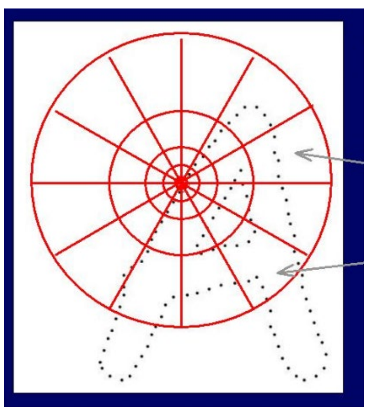

4x4 location grid and 8 orientations (128 dimensions)

very good performance in image matching [Mikolaczyk and Schmid'03]

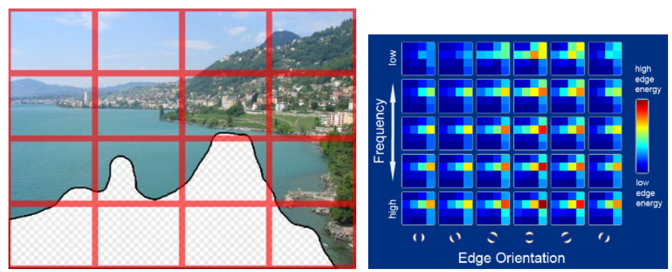
# Gradient Histograms pop-up everywhere



HOG descriptor



Generalized Shape Context



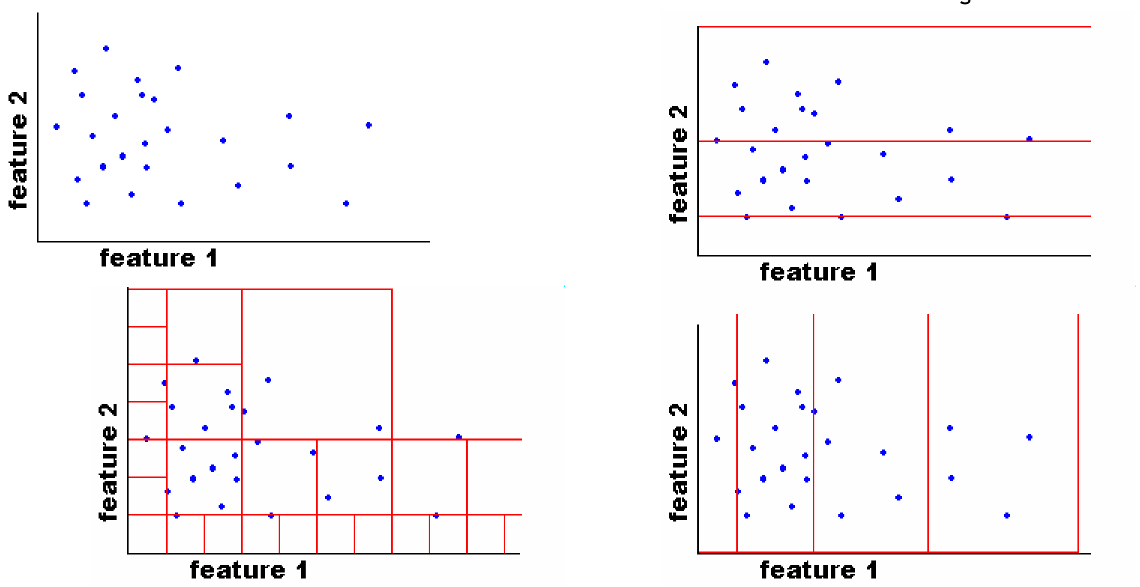

Gist Descriptor

Freeman and Roth IAFGR 1995
Lowe ICCV1999
Oliva & Torralba, 2001
Belongie et al, 2001
Dalal &Triggs CVPR05

Binning achieves invariance to small patch offsets

# Adaptive Representations

Images from Dave

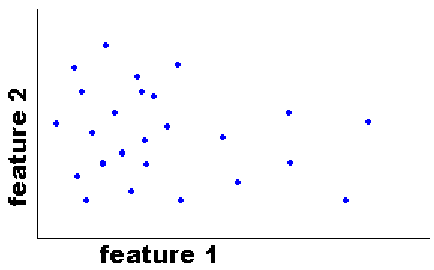


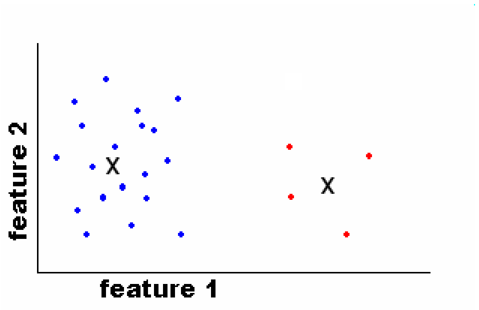

Adaptive binning

- Better data/bin distribution, fewer empty bins
- Can adapt available resolution to relative feature importance

# Clustering: very adaptive representations

Images from Dave Kauchak

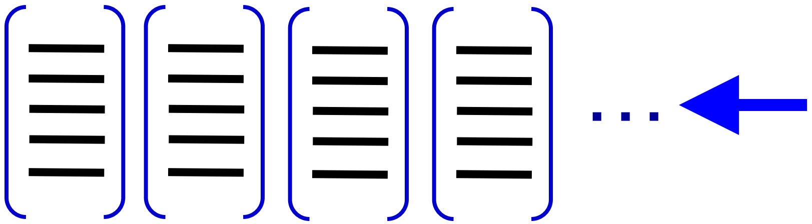


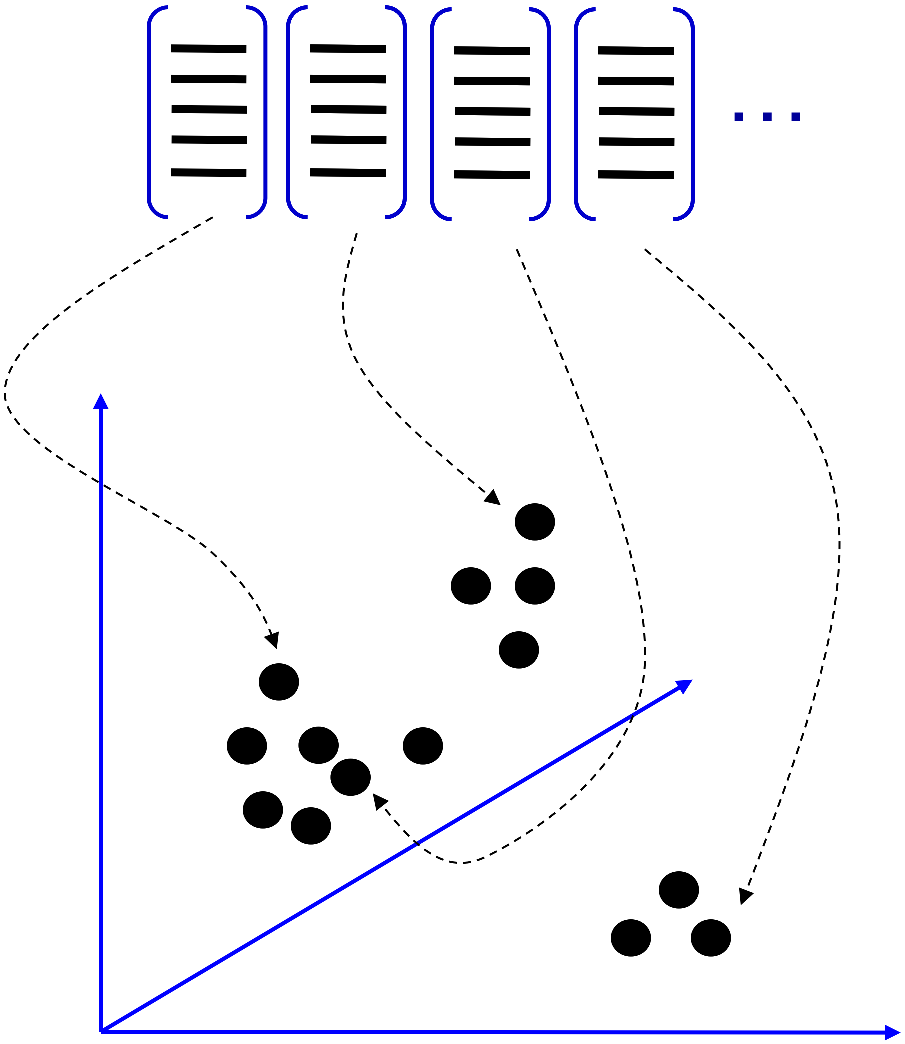

Clusters / Signatures

- “super-adaptive” binning
- Does not require discretization along any fixed axis

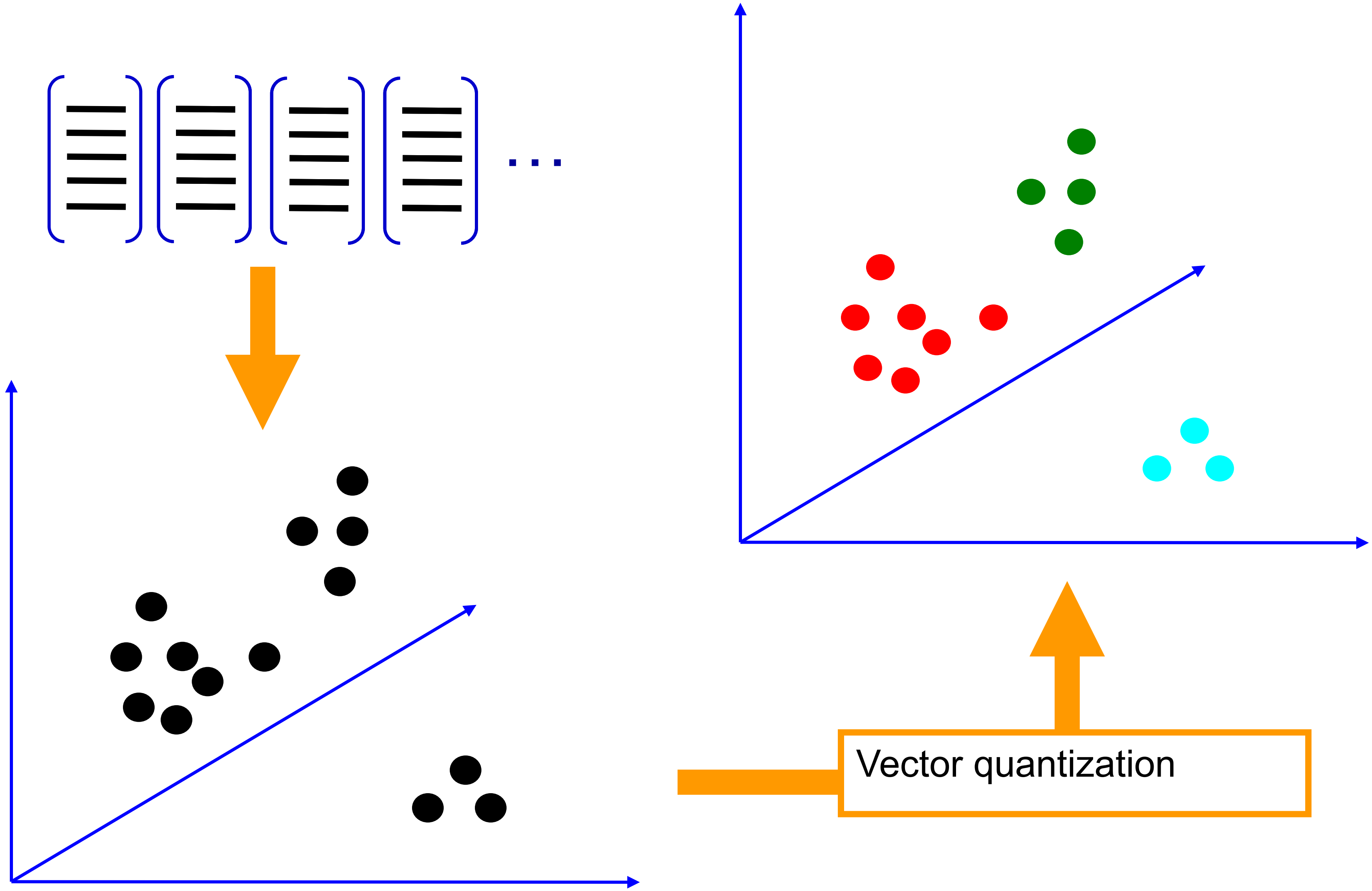
# Patch Features



# dictionary formation

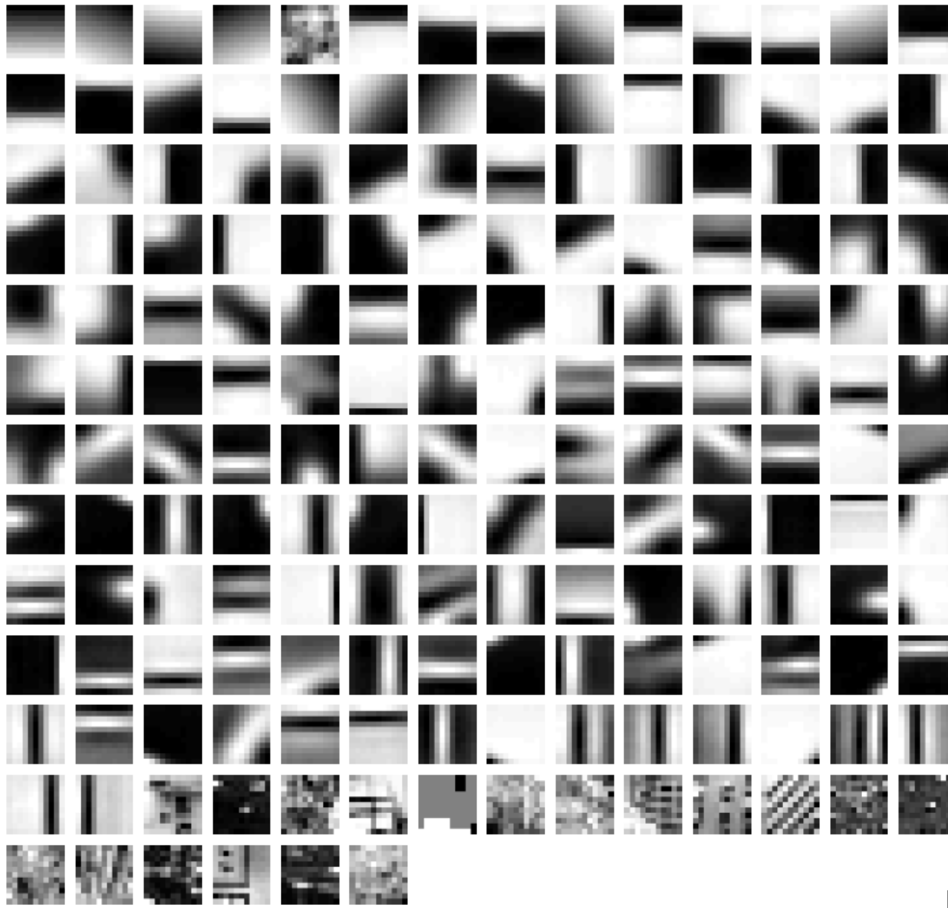


# Clustering (usually k-means)



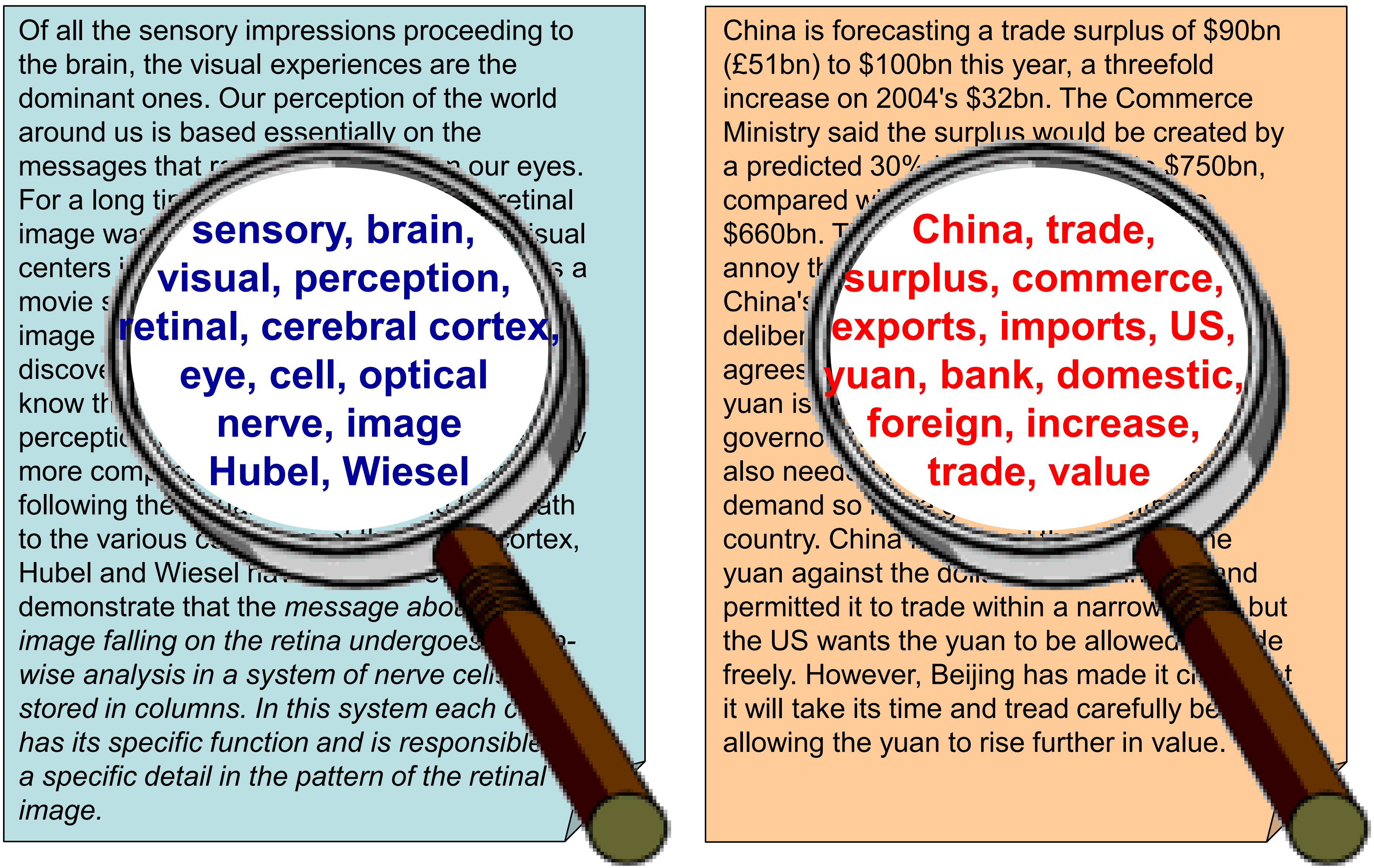

Slide credit: Josef Sivic

# Clustered Image Patches ("Bag of Visual Words")

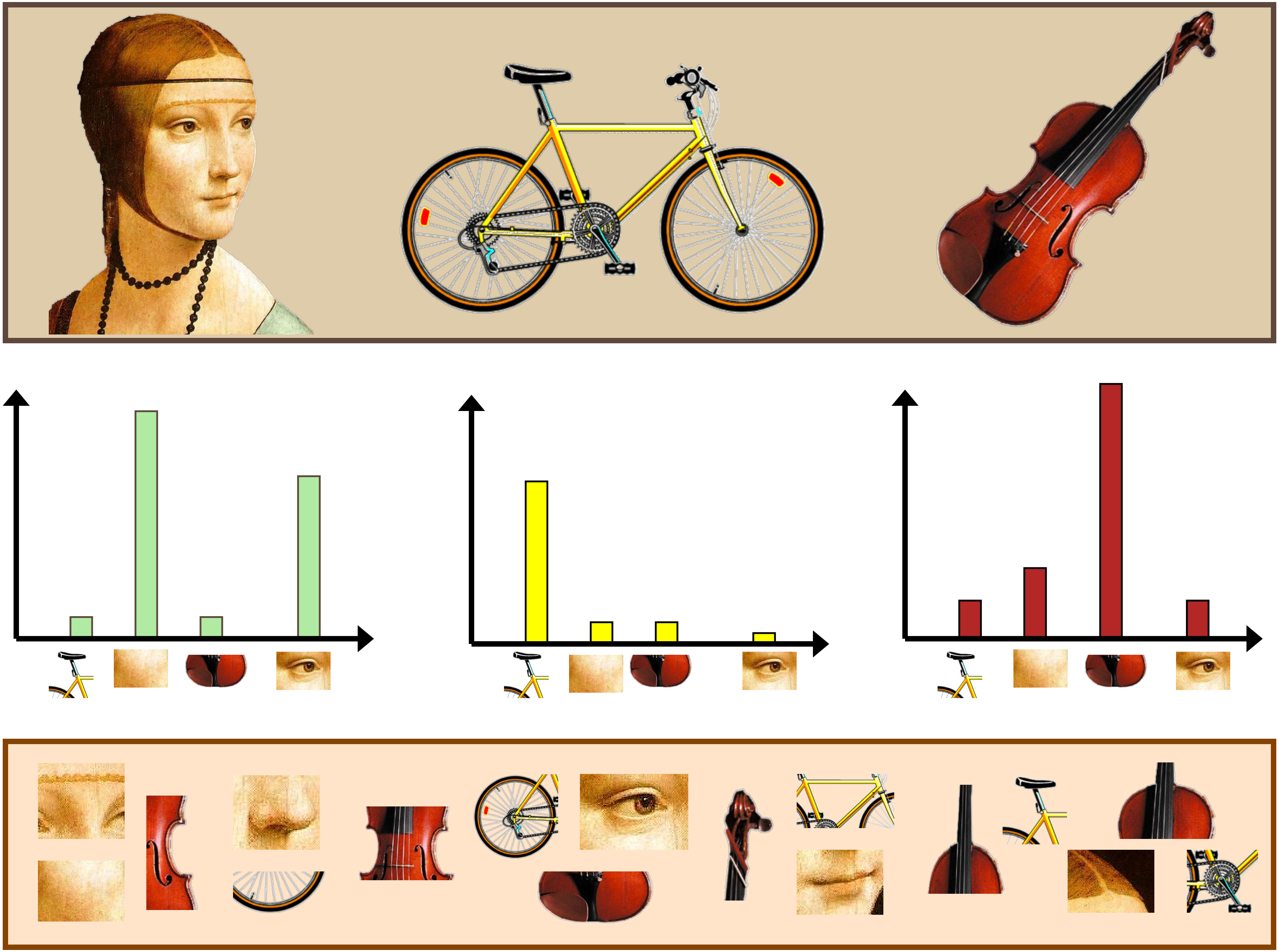


Fei-Fei et al. 2005

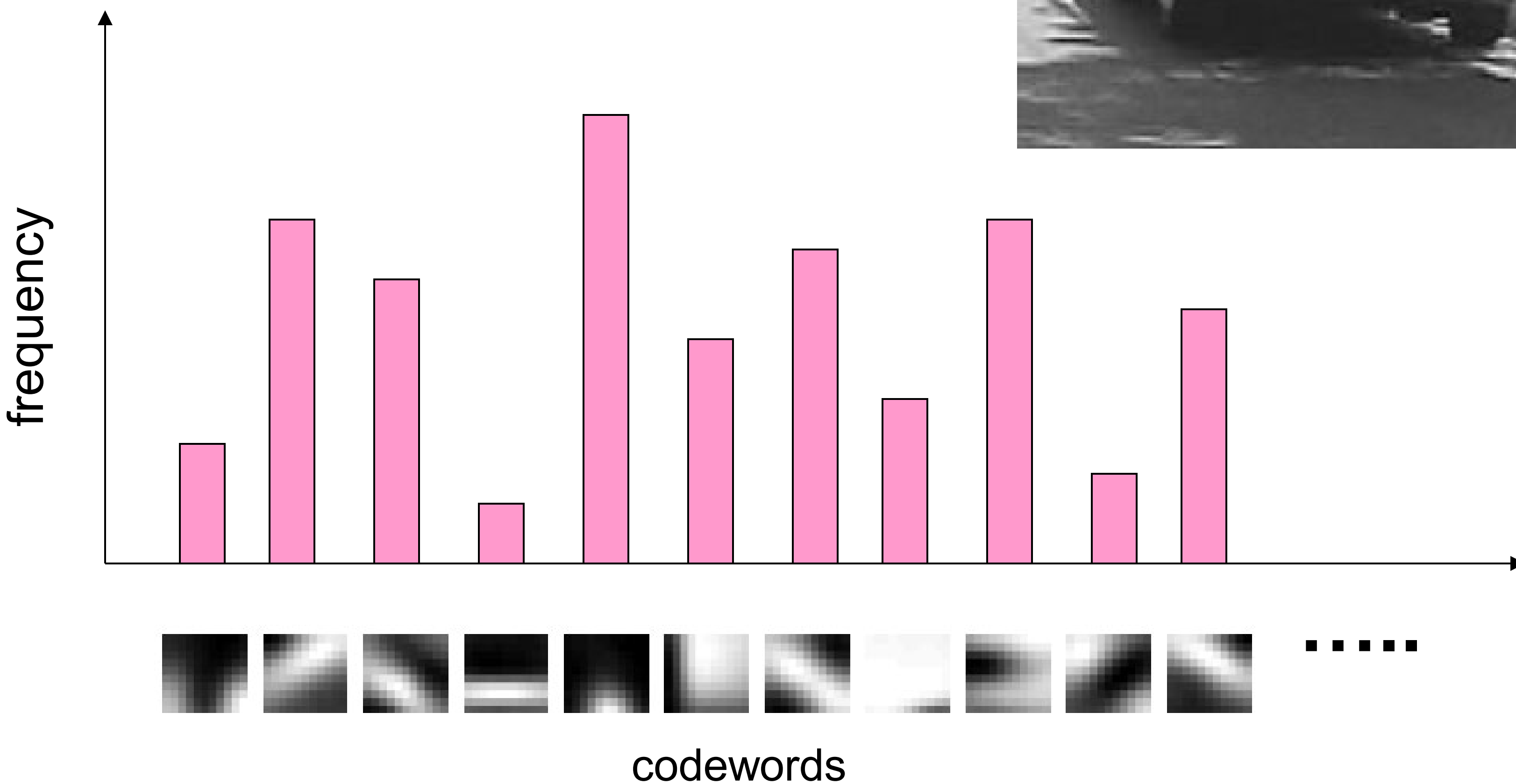
# Analogy to documents



Object → Bag of ‘words’



# Image representation



# Scene Classification (Renninger & Malik)

beach

mountain

forest

city

street

farm

kitchen

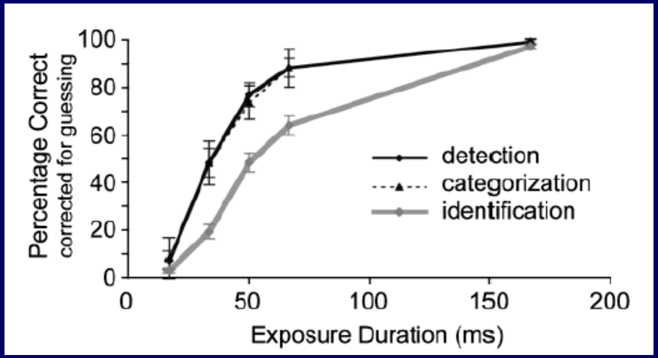
livingroom

bedroom

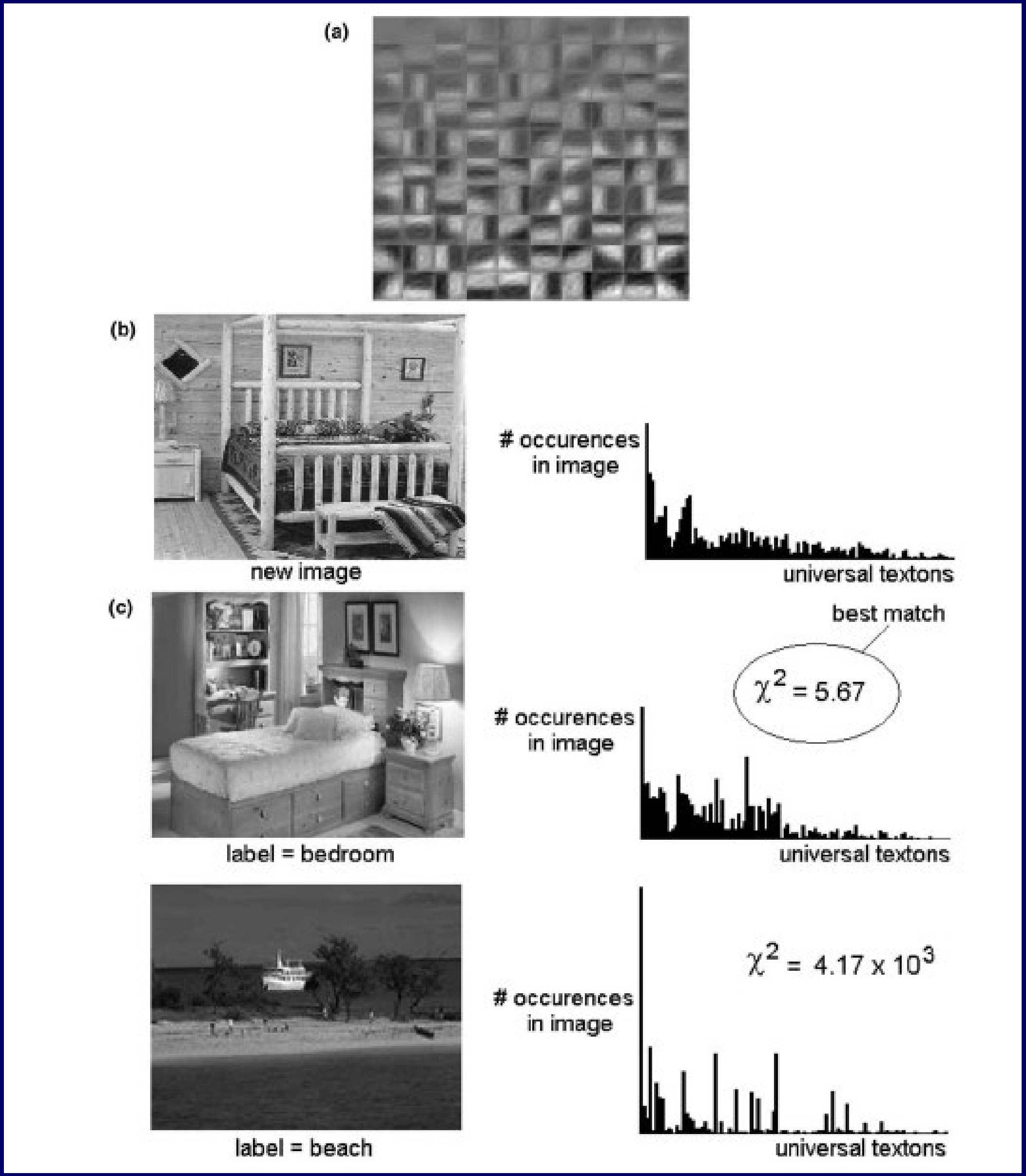
bathroom

# Image classification can be pre-attentive!

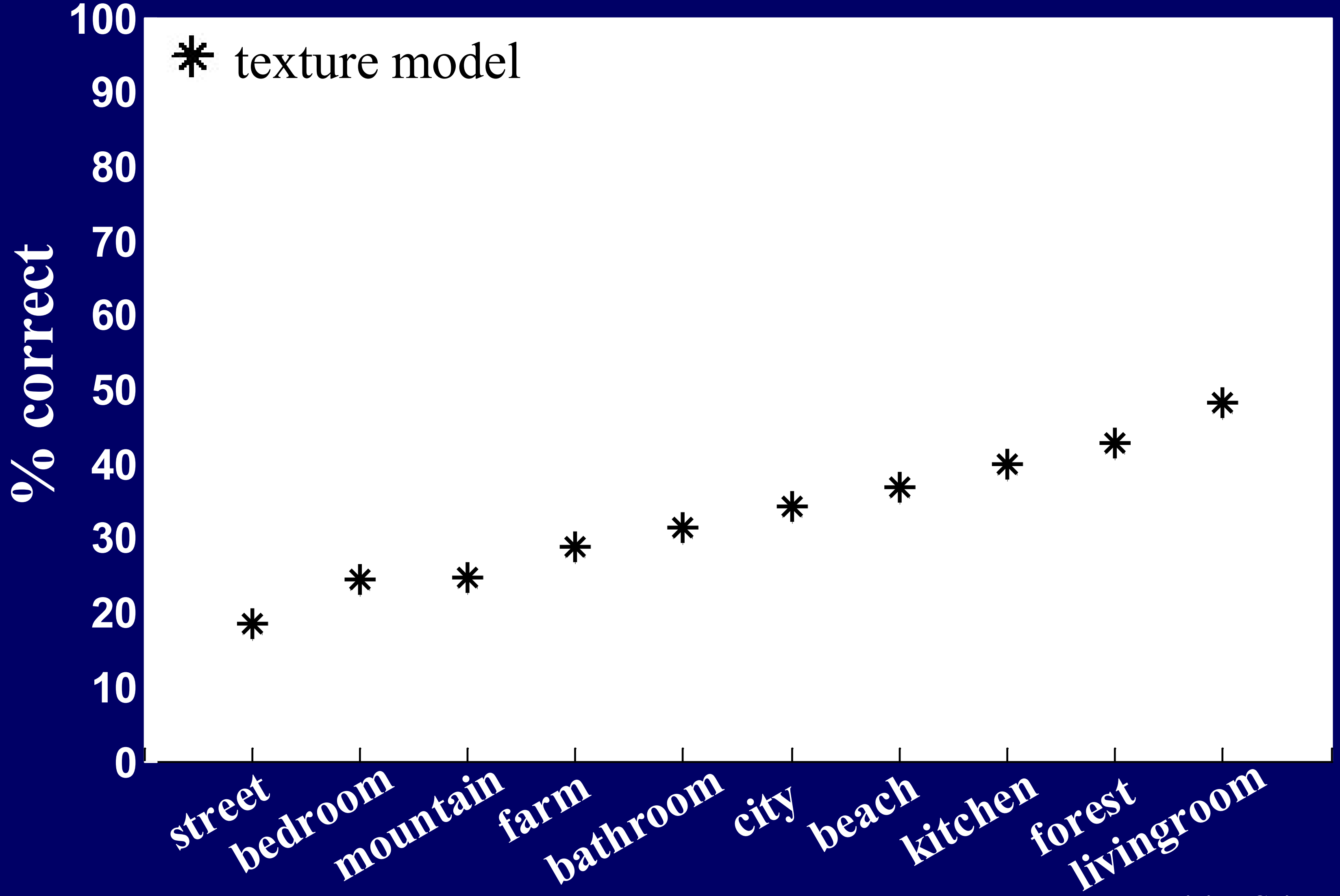
- On a task of judging animal vs no animal, humans can make mostly correct saccades in 150 ms (Kirchner & Thorpe, 2006)
  - Comparable to synaptic delay in the retina, LGN, V1, V2, V4, IT pathway.
  - Doesn't rule out feed back but shows feed forward only is very powerful
- Detection and categorization are practically simultaneous (Grill-Spector & Kanwisher, 2005)



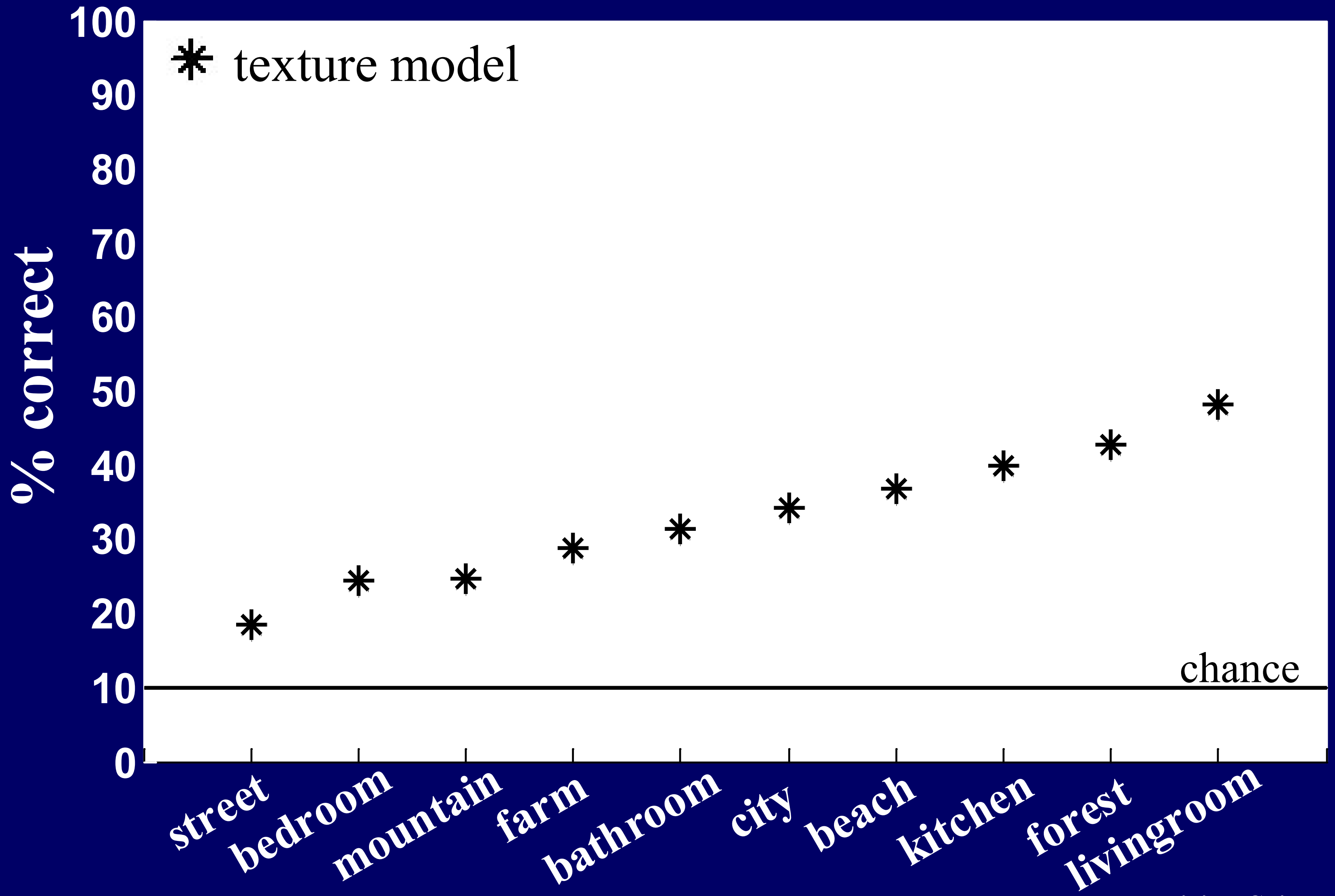
# Texton Histogram Matching



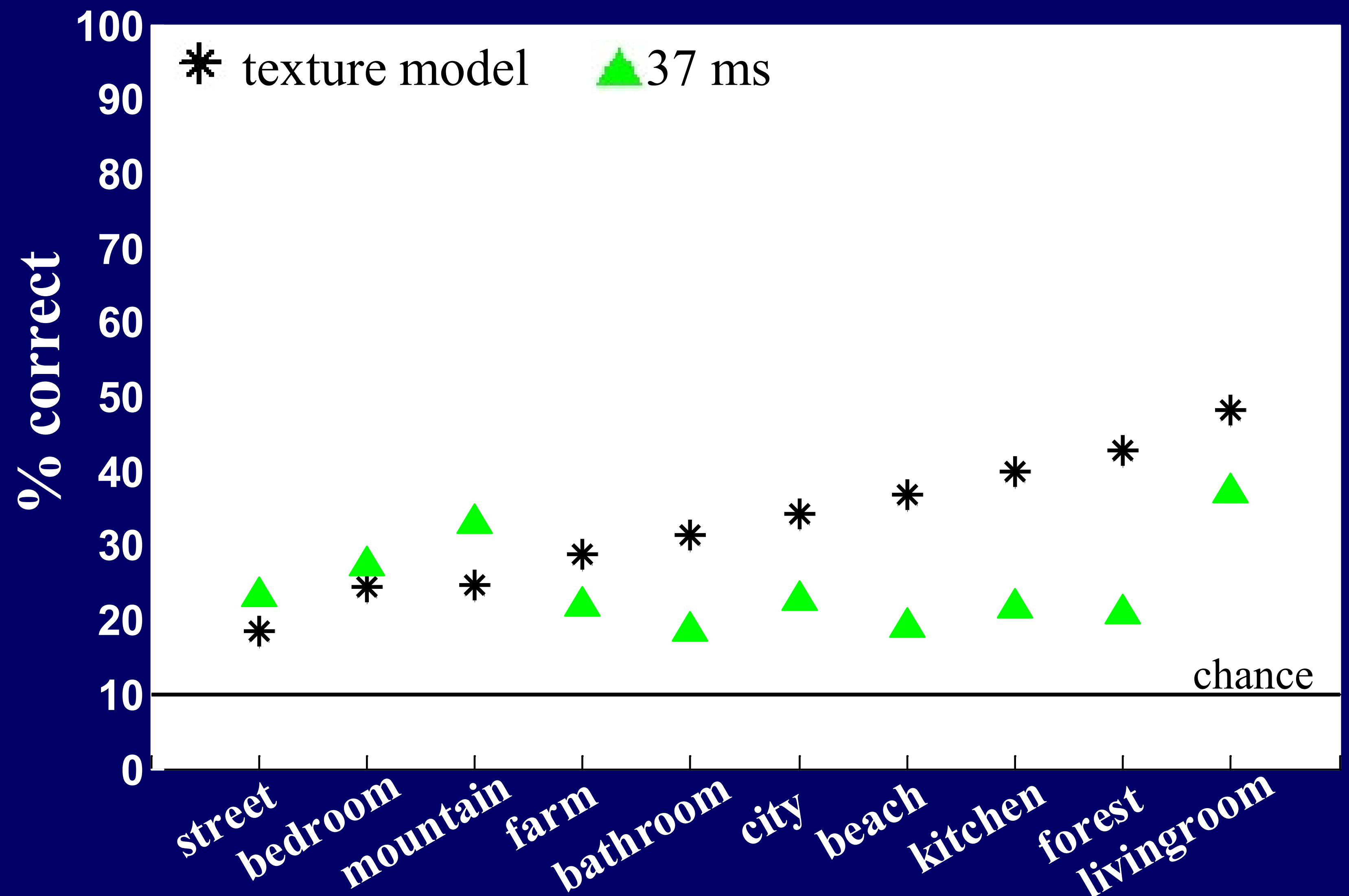
# Discrimination of Basic Categories



# Discrimination of Basic Categories



# Discrimination of Basic Categories



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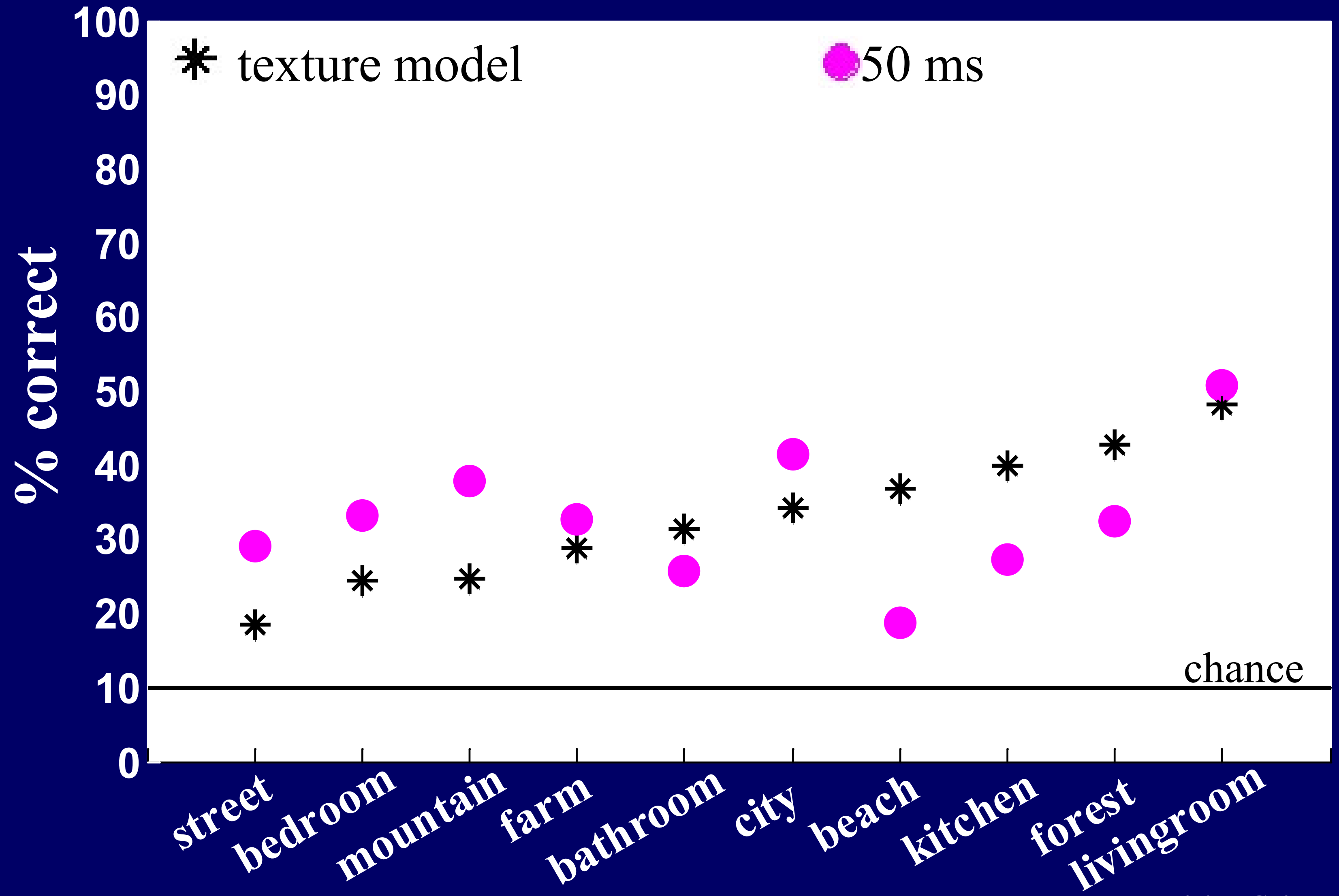
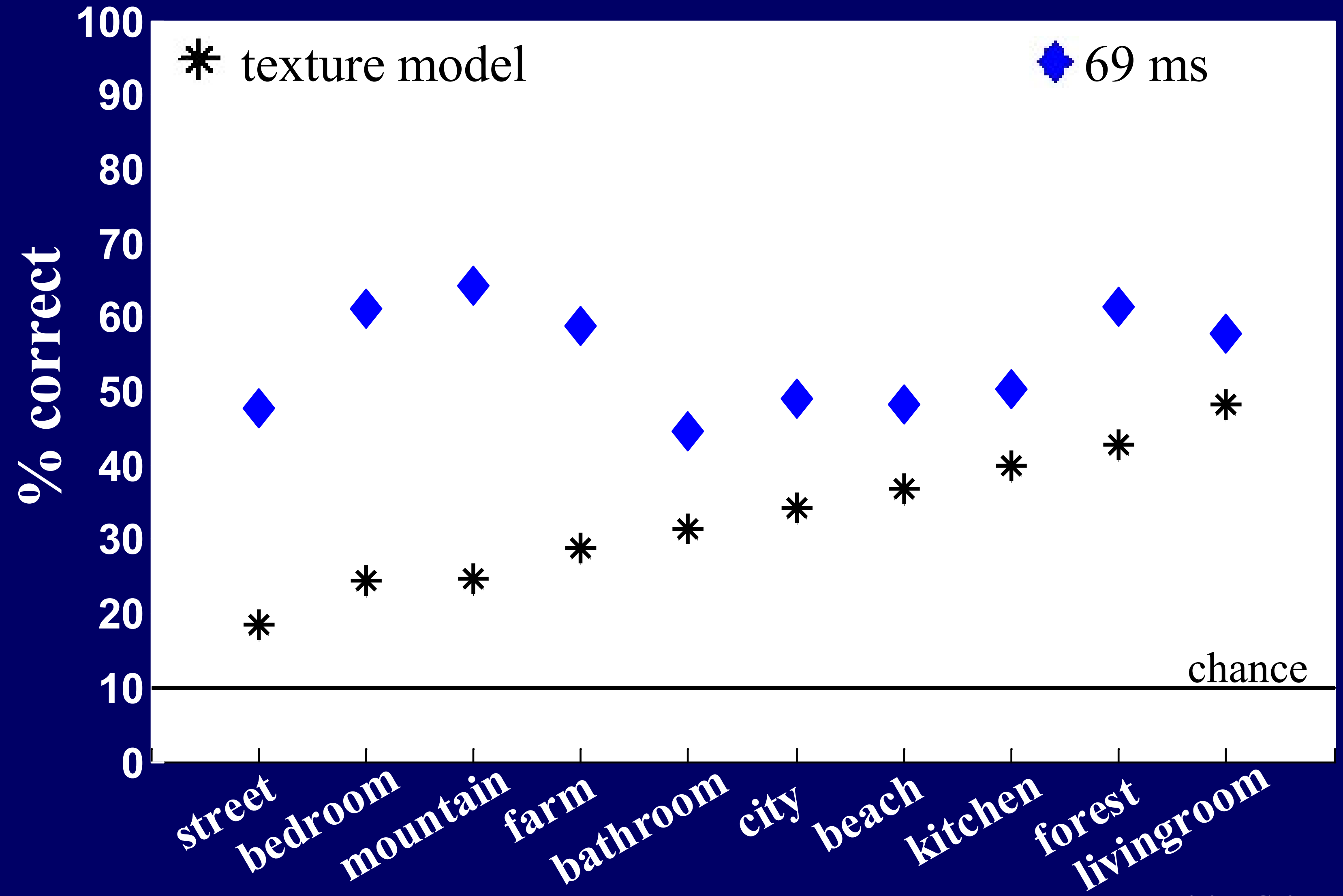
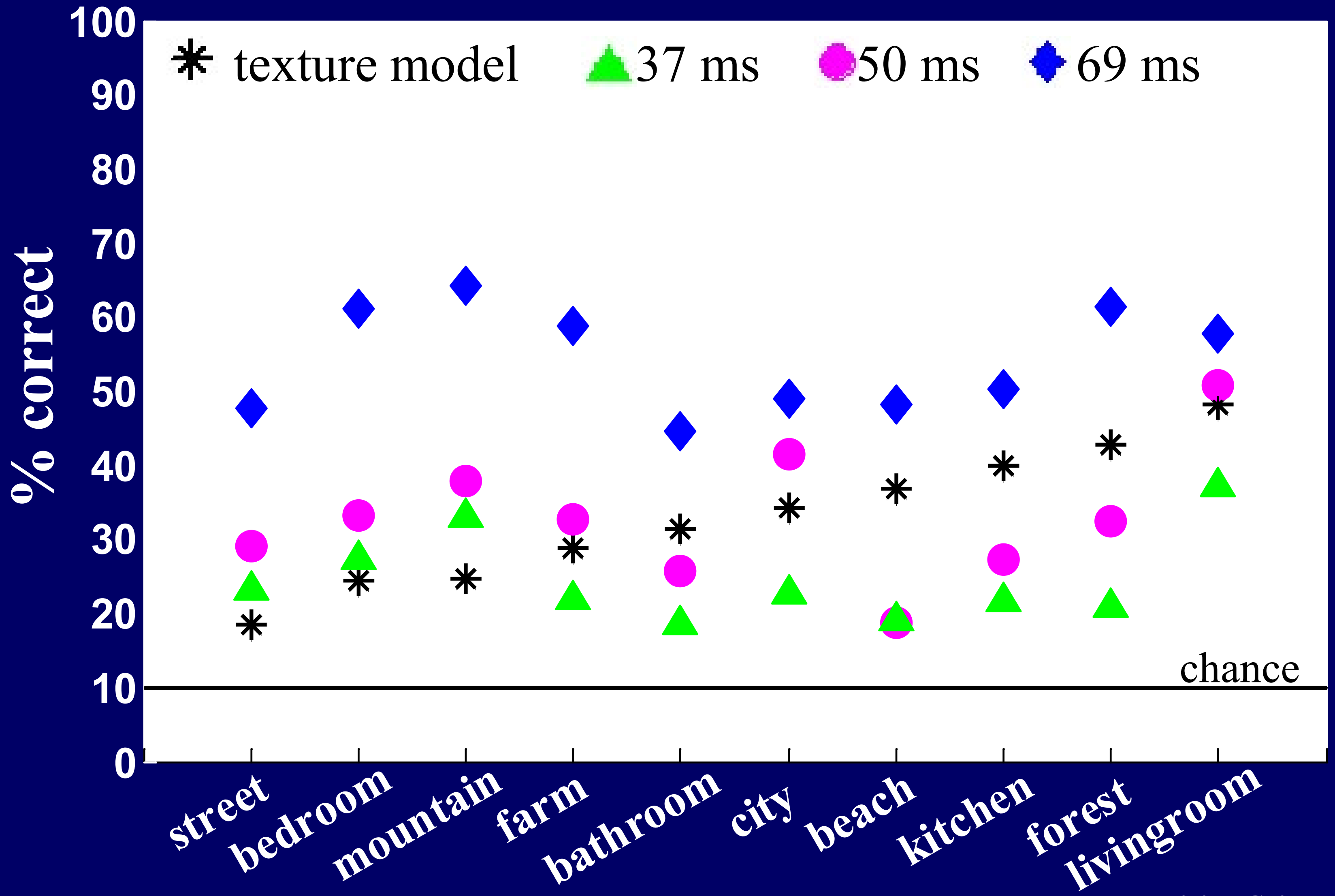


# Discrimination of Basic Categories



# Discrimination of Basic Categories

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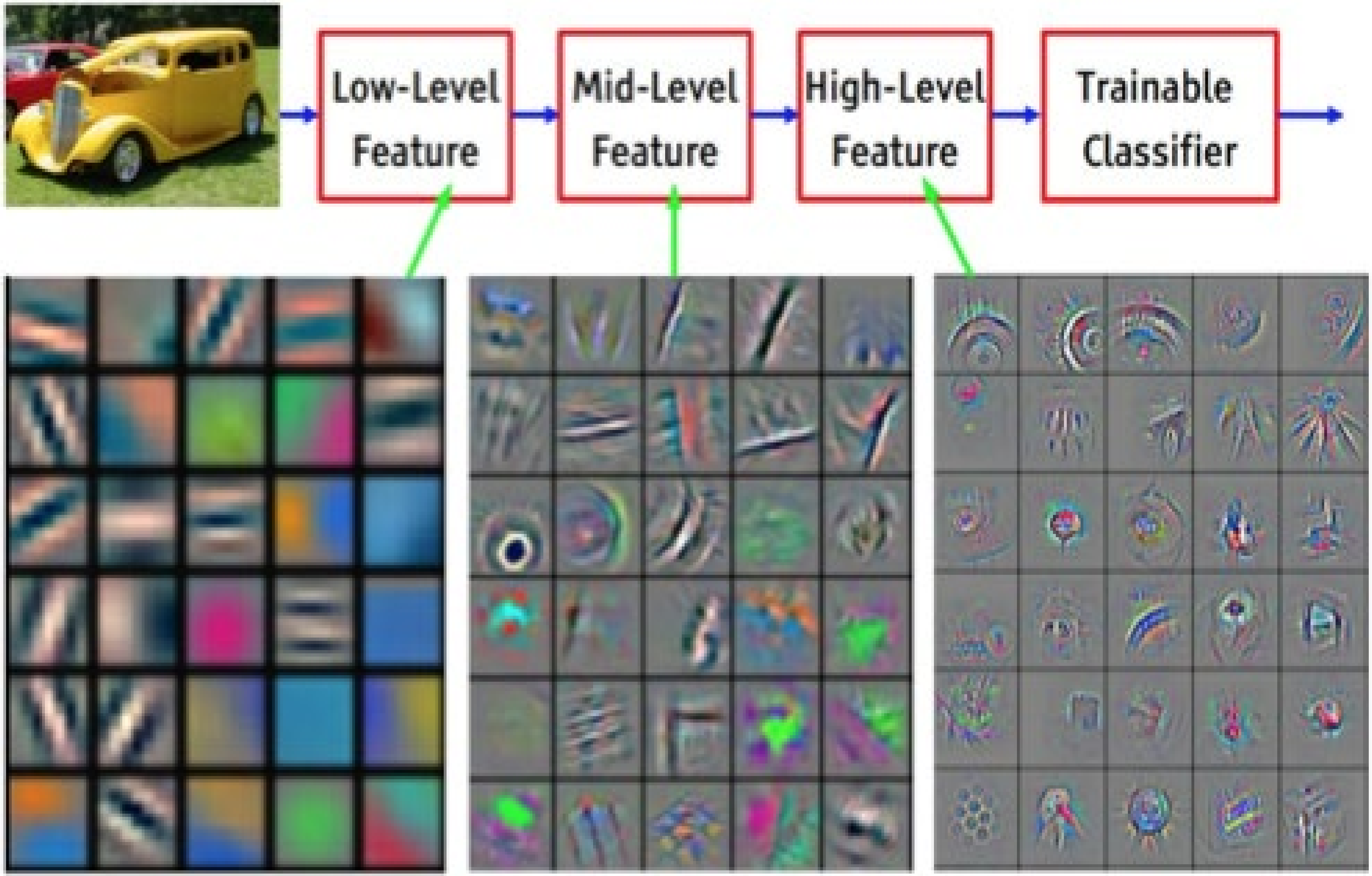
# Scene Recognition using Texture

# Convolutional Neural Networks




Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]