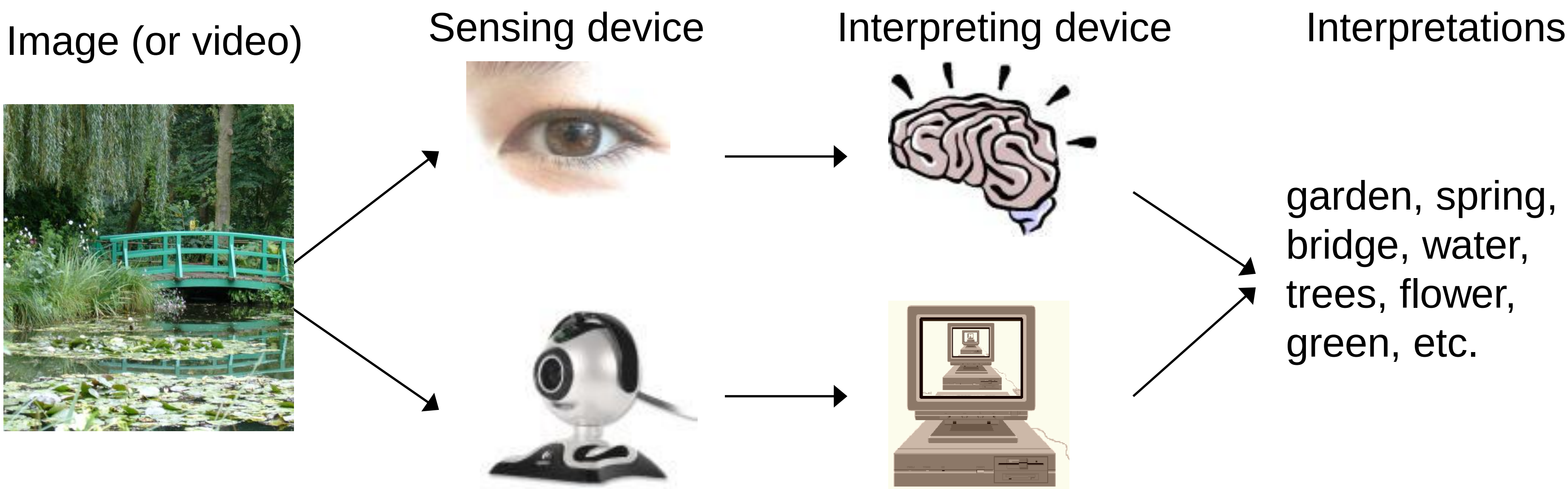
Computer Vision for Robotics

What are “Autonomous Robots”?

- Mobile machines with power, sensing, and computing on-board
- Environments
  - Land (on and under)
  - Water (ditto)
  - Air
  - Space
  - ???

What is (computer) vision?



Computer vision vs human vision

0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

What we see

What a computer sees

What Skills Do Robots Need?

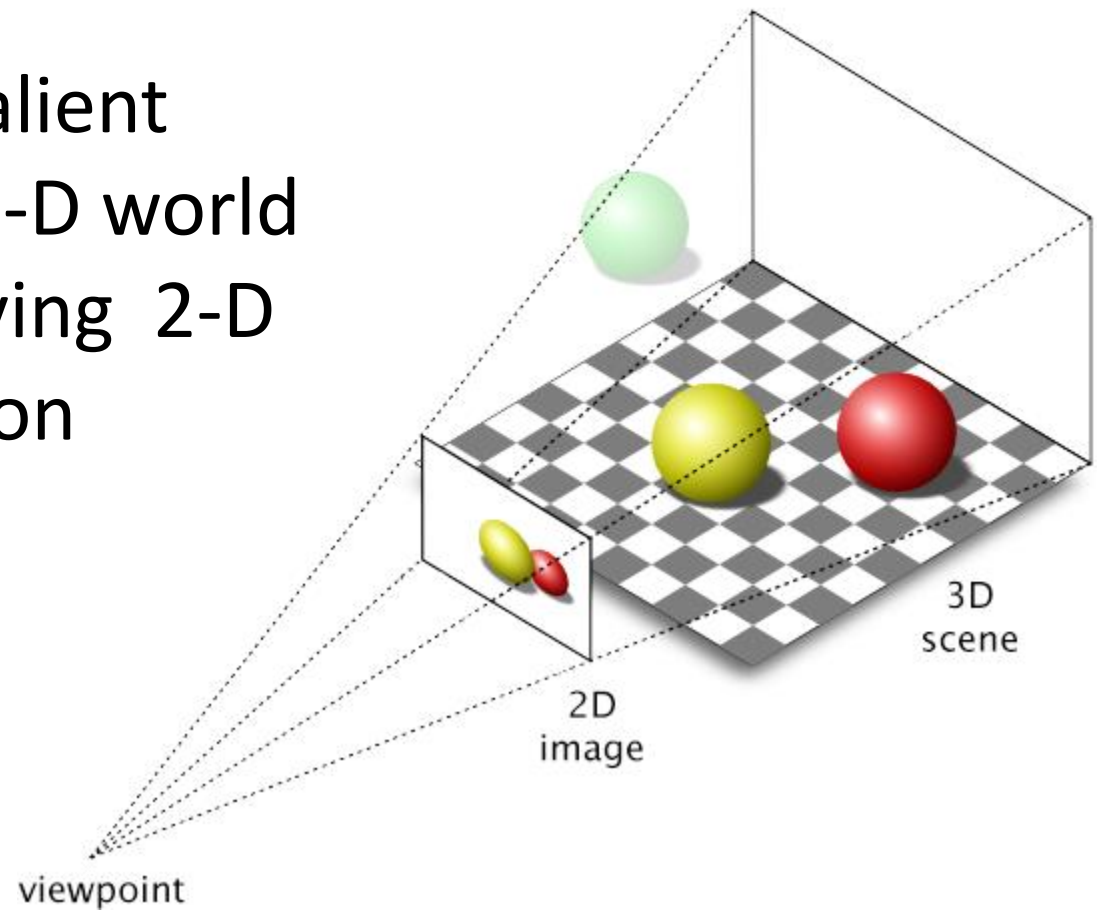
- **Identification**: *What/who is that?*
  - Object detection, recognition
- **Movement**: *How do I move safely?*
  - Obstacle avoidance, homing
- **Manipulation**: *How do I change that?*
  - Interacting with objects/environment
- **Navigation**: *Where am I?*
  - Mapping, localization

Why Vision?

- Pluses
  - Rich stream of complex information about the environment
  - Primary human sense
  - Good cameras are fairly cheap
  - Passive $\rightarrow$ stealthy
- Minuses
  - Line of sight only
  - Passive $\rightarrow$ Dependent on ambient illumination

The Vision Problem

How to infer salient properties of 3-D world from time-varying 2-D image projection



Computer Vision Outline

- Image formation
- Image processing
- Motion & Estimation
- Classification & Clustering

Outline: Image Formation

- 3-D geometry
- Physics of light
- Camera properties
  - Focal length
  - Distortion
- Sampling issues
  - Spatial
  - Temporal

Outline: Image Processing

- Filtering
  - Edge
  - Color
  - Shape
  - Texture
- Feature detection
- Pattern comparison

Outline: Motion & Estimation

- Computing temporal image change
  - Magnitude
  - Direction
- Fitting parameters to data
  - Static
  - Dynamic (e.g., tracking)
- Applications
  - Motion Compensation
  - Structure from Motion

Outline: Classification & Clustering

- Categorization
  - Assignment to known groups
- Clustering
  - Inference of group existence from data
  - Special case: Segmentation

Visual Skills: Identification

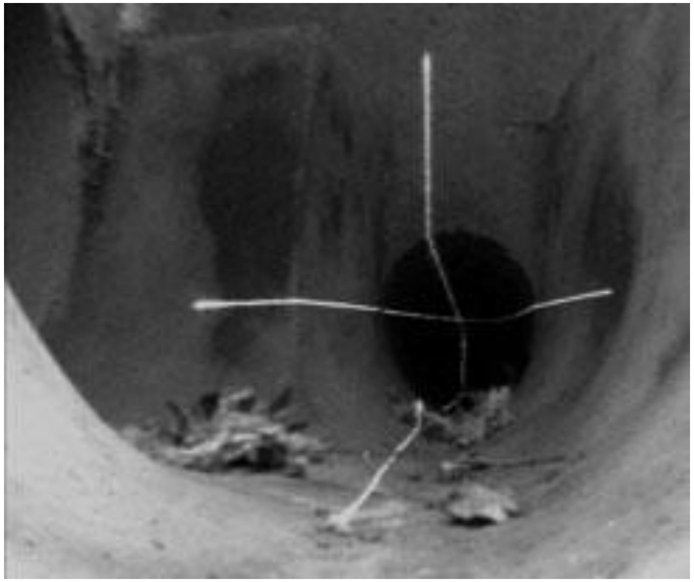
- Recognizing face/body/structure: *Who/what do I see?*
  - Use shape, color, pattern, other static attributes to distinguish from background, other hypotheses
- Gesture/activity: *What is it doing?*
  - From low-level motion detection & tracking to categorizing high-level temporal patterns
- Feedback between static and dynamic

Minerva Face Detection

Finding people to interact with

Visual Skills: Movement

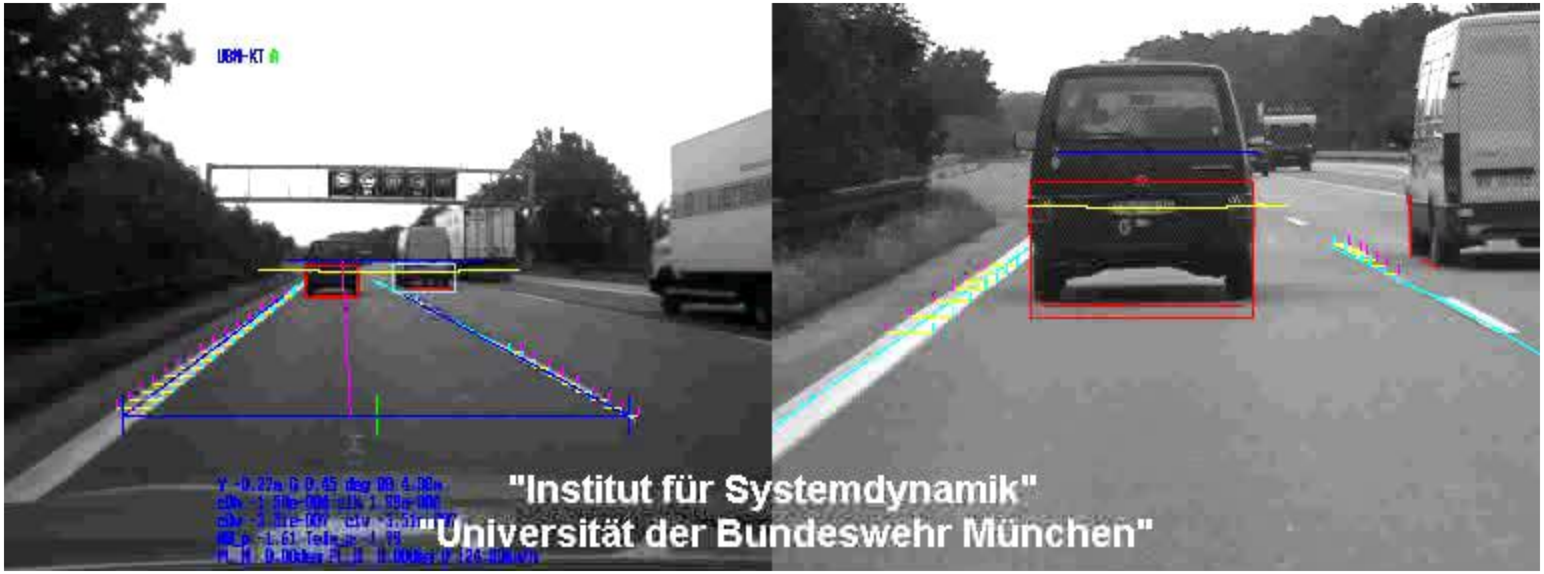
- Steering, foot placement or landing spot for entire vehicle



MAKRO sewer shape pattern

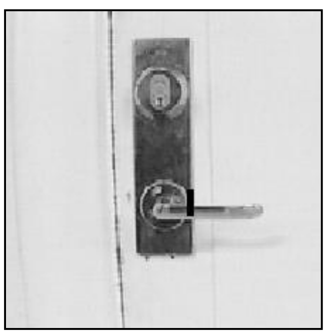
Demeter region boundary detection

UBM Lane & vehicle tracking (with radar)



Visual Skills: Manipulation

- Moving other things
  - Grasping: Door opener (KTH)
  - Pushing, digging, cranes

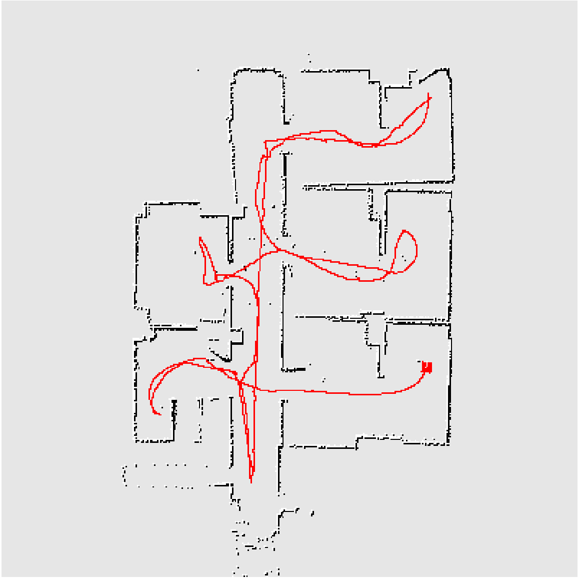


KTH robot & typical handle

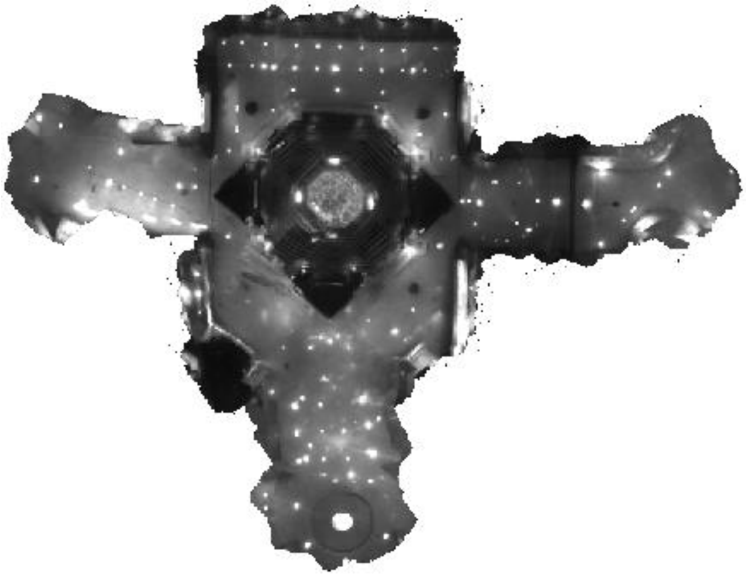
Clodbusters push a box cooperatively

Visual Skills: Navigation

- Building a map
- Localization/place recognition
  - *Where are you in the map?*



Laser-based wall map (CMU)

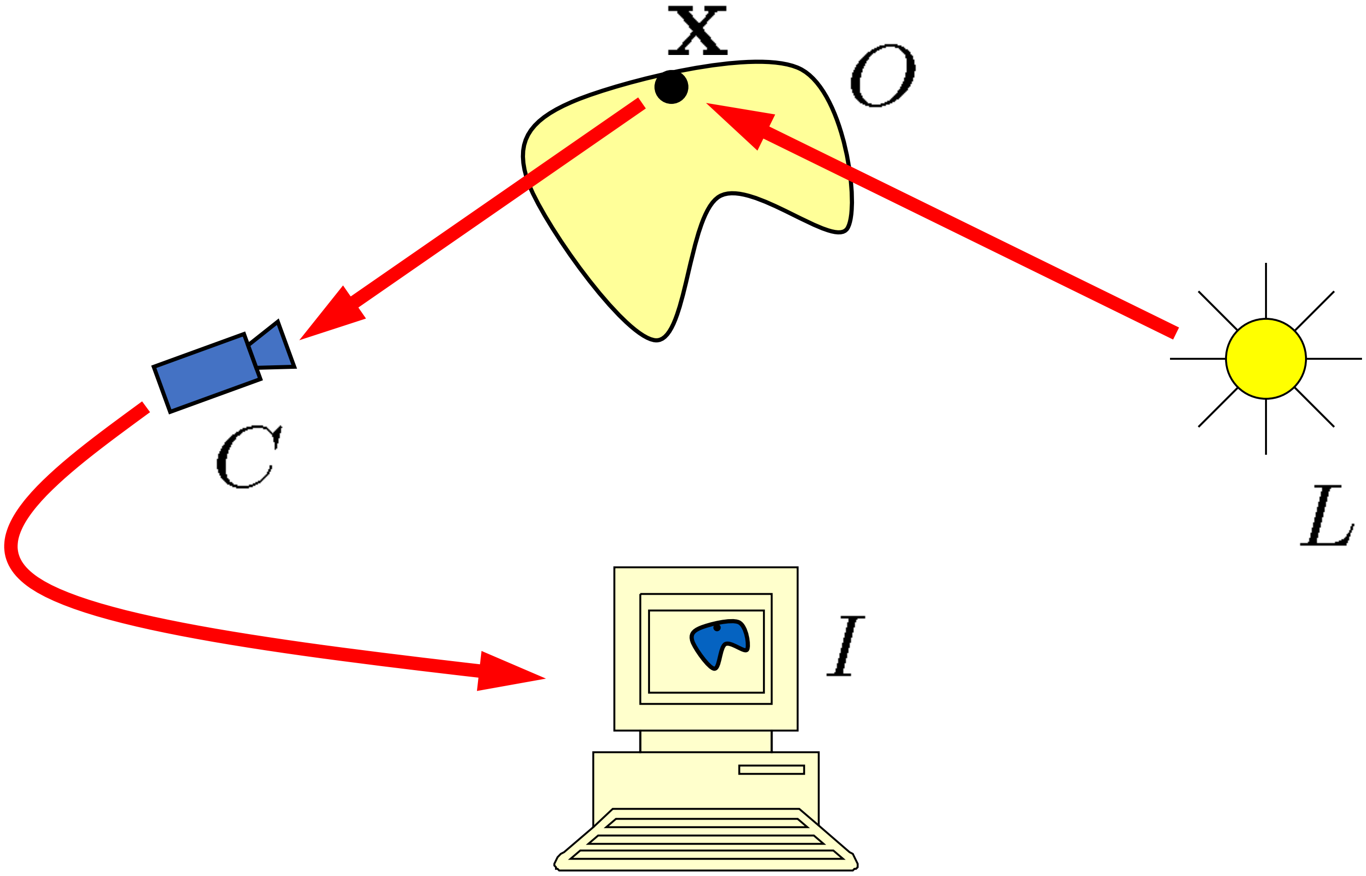


Minerva's ceiling map

Outline: Image Formation

- Geometry
  - Coordinate systems, transformations
  - Perspective projection
  - Lenses
- Radiometry
  - Light emission, interaction with surfaces
- Analog $\rightarrow$ Digital
  - Spatial sampling
  - Dynamic range
  - Temporal integration

The Image Formation Pipeline



Coordinate System Conventions

- $\mathbf{i}, \mathbf{j}, \mathbf{k}$ unit vectors along positive $\mathbf{k} = \mathbf{i} \times \mathbf{j}$ axes, X, Y, Z respectively;
- Right- vs. left-handed coordinates
- Local coordinate systems: camera, world, etc.

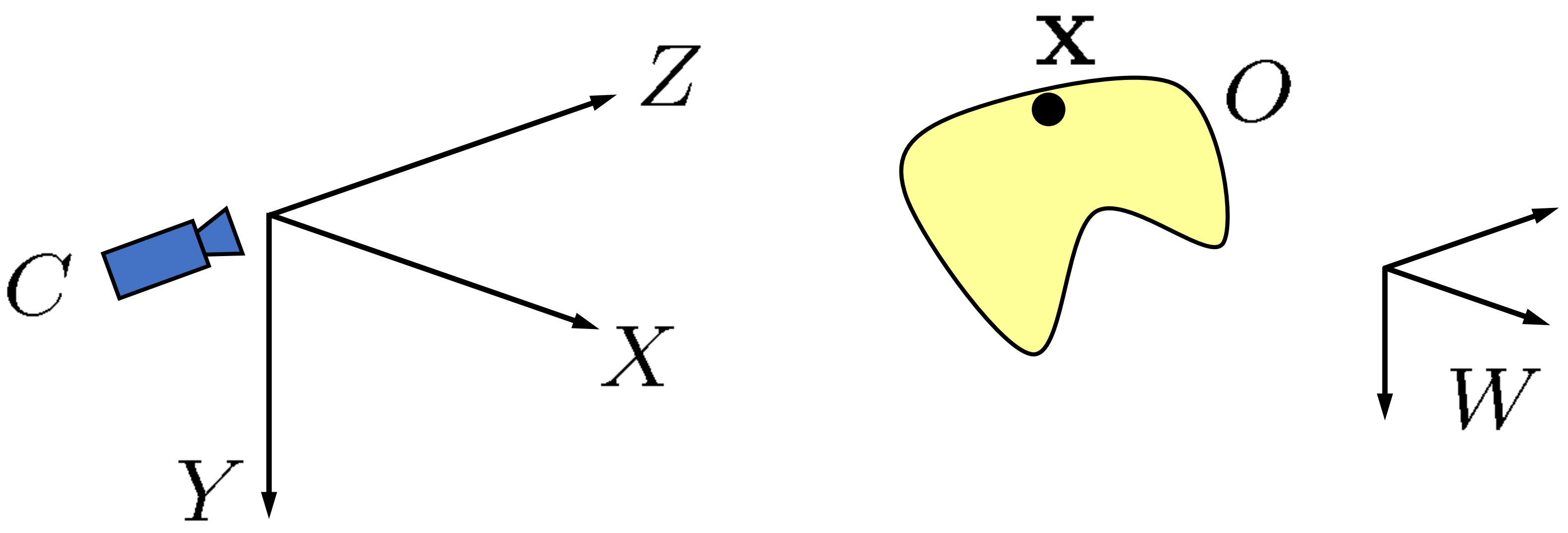


Image Processing Outline

- Images
- Binary operators
- Filtering
  - Smoothing
  - Edge, corner detection
- Modeling, matching
- Scale space

Images

- An image is a matrix of pixels $\mathbf{I}(x, y)$
- Resolution
  - Digital cameras: 1600 X 1200 at a minimum
  - Video cameras: ~640 X 480
- Grayscale: generally 8 bits per pixel $\rightarrow$ Intensities in range [0…255]
- RGB color: 3 8-bit color planes $\mathbf{I}_R, \mathbf{I}_G, \mathbf{I}_B$

Image Conversion

- RGB $\rightarrow$ Grayscale: Mean color value, or weight by perceptual importance

- Grayscale $\rightarrow$ Binary: Choose threshold based on histogram of image intensities

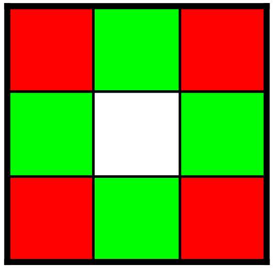
Color Representation

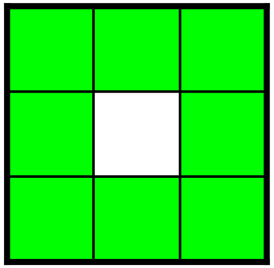
- RGB, HSV (hue, saturation, value), YUV, etc.
- Luminance: Perceived intensity
- Chrominance: Perceived color
  - HS(V), (Y)UV, etc.
  - Normalized RGB removes some illumination dependence:

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}$$

Binary Operations

- Dilation, erosion
  - Dilation: All 0's next to a 1 $\rightarrow$ 1 (Enlarge foreground)
  - Erosion: All 1's next to a 0 $\rightarrow$ 0 (Enlarge background)
- Connected components
  - Uniquely label each *n*-connected region in binary image
  - 4- and 8-connectedness





- Moments: Region statistics
  - Zeroth-order: Size
  - First-order: Position (centroid)
  - Second-order: Orientation

Image Transformations

- Geometric: Compute new pixel locations
  - Rotate
  - Scale
  - Undistort (e.g., radial distortion from lens)

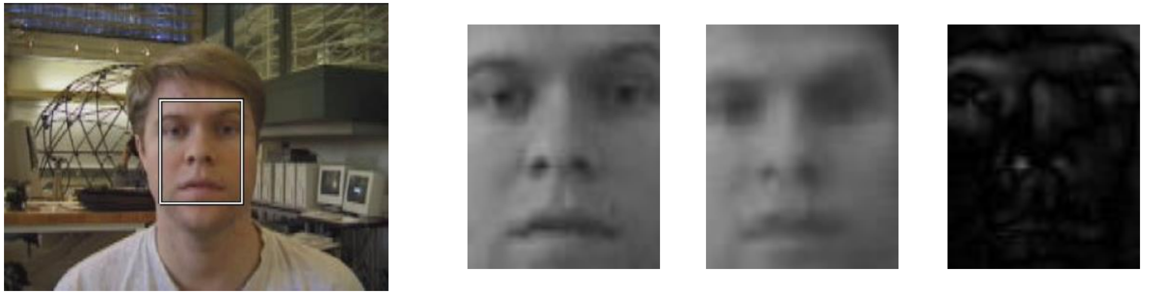
$$\boxed{T(x, y) \rightarrow (x', y')}$$

- Photometric: How to compute new pixel values when $T^{-1}(x', y')$ non-integral
  - Nearest neighbor: Value of closest pixel
  - Bilinear interpolation (2 x 2 neighborhood)
  - Bicubic interpolation (4 x 4)

Image Comparison: SSD

- Given a template image $\mathbf{I}_T$ and an image $\mathbf{I}$, how to quantify the similarity between them for a given alignment?
- Sum of squared differences (SSD)

$$\sum_{x,y}[\mathbf{I}_T(x,y) - \mathbf{I}(x,y)]^2$$



Cross-Correlation for Template Matching

- Note that SSD formula can be written:

$$\sum_{x,y} \mathbf{I}_T^2(x,y) + \mathbf{I}^2(x,y) - 2\mathbf{I}_T(x,y)\mathbf{I}(x,y)$$

- First two terms fixed $\rightarrow$ last term measures mismatch—the *cross-correlation:*

$$\sum_{x,y} \mathbf{I}_T(x,y) \cdot \mathbf{I}(x,y)$$

- In practice, normalize by image $\mathbf{I}$ magnitude when shifting template to search for matches

Filtering

- Idea: Analyze neighborhood around some point in image f with filter function h ; put result in new image at corresponding location g
- System properties
  - Shift invariance: Same inputs give same outputs, regardless of location
  - Superposition: Output on sum of images =
  - Sum of outputs on separate images
  - Scaling: Output on scaled image = Scaled output on image
- Linear shift invariance $\rightarrow$ **Convolution**

Discrete Filtering

- Linear filter: Weighted sum of pixels over rectangular neighborhood—*kernel* defines weights
- Think of kernel as template being matched by correlation
- Convolution: Correlation with kernel rotated 180°
- Dealing with image edges
  - Zero-padding
  - Border replication

1	-1	-1
1	2	-1
1	1	1

Filtering Example 1:

$$\mathbf{I}' = \mathbf{K} * \mathbf{I}$$

$\mathbf{K}$

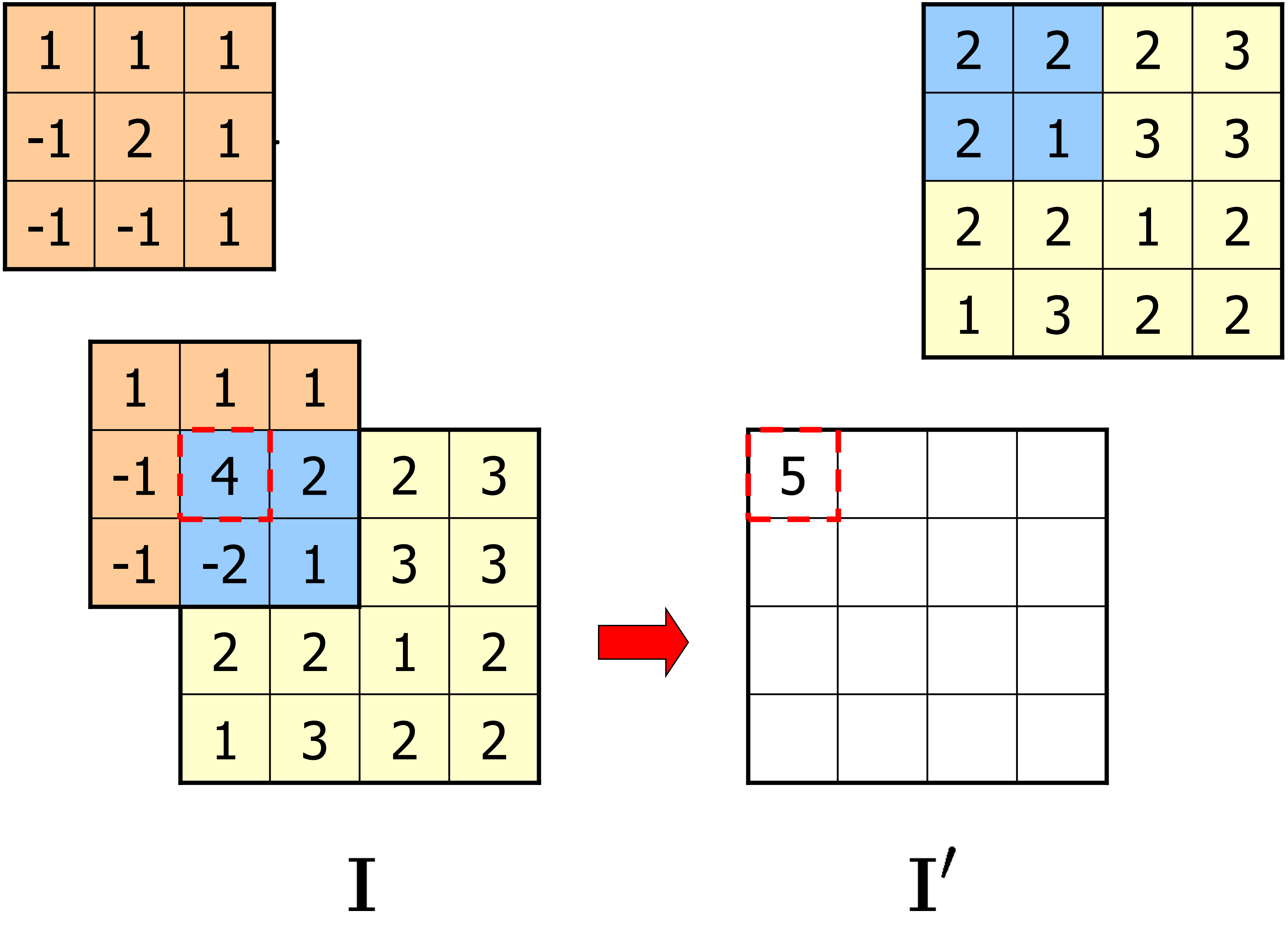
1	-1	-1
1	2	-1
1	1	1

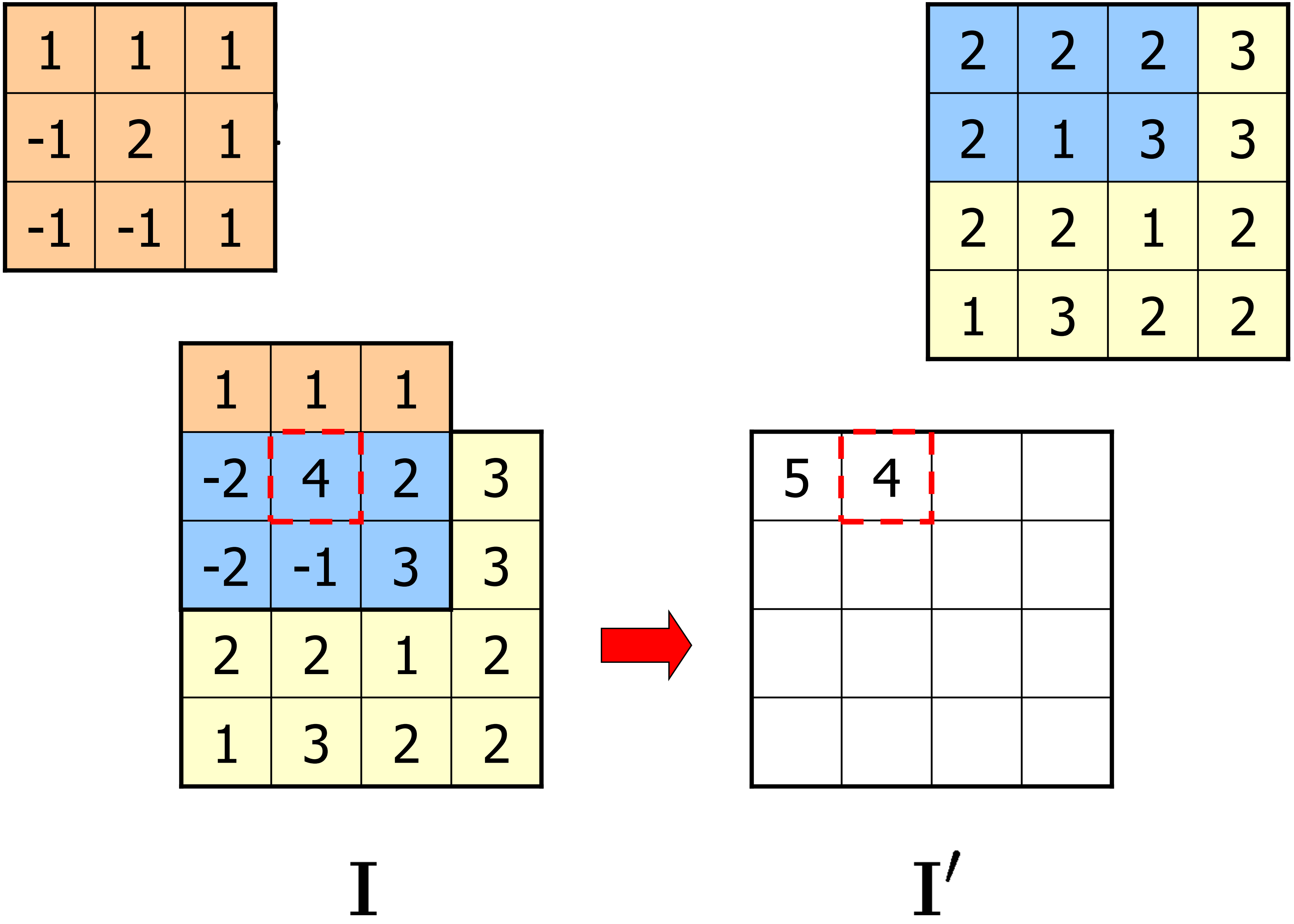
Rotate

1	1	1
-1	2	1
-1	-1	1

$\mathbf{I}$

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2


I
I′


I
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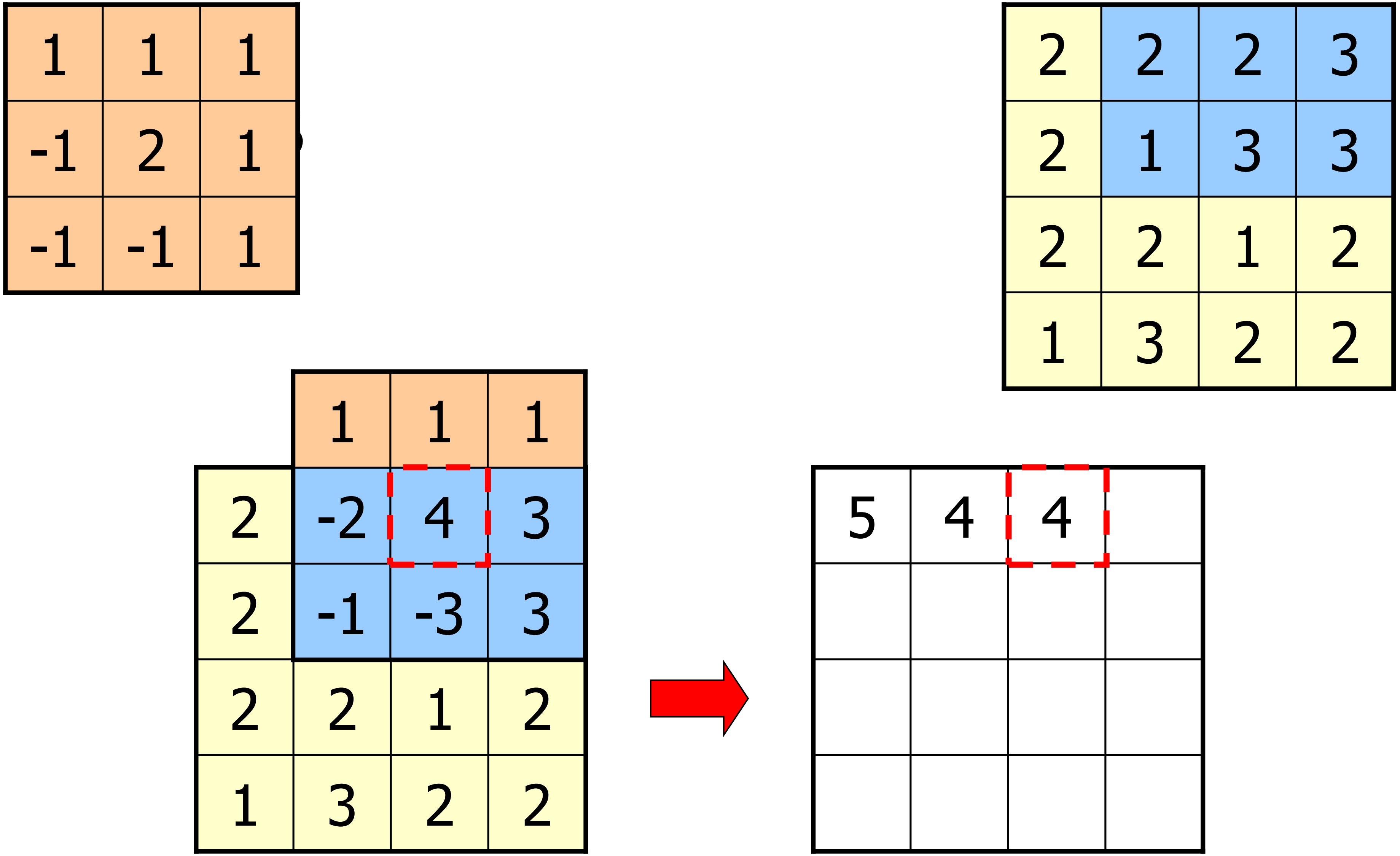
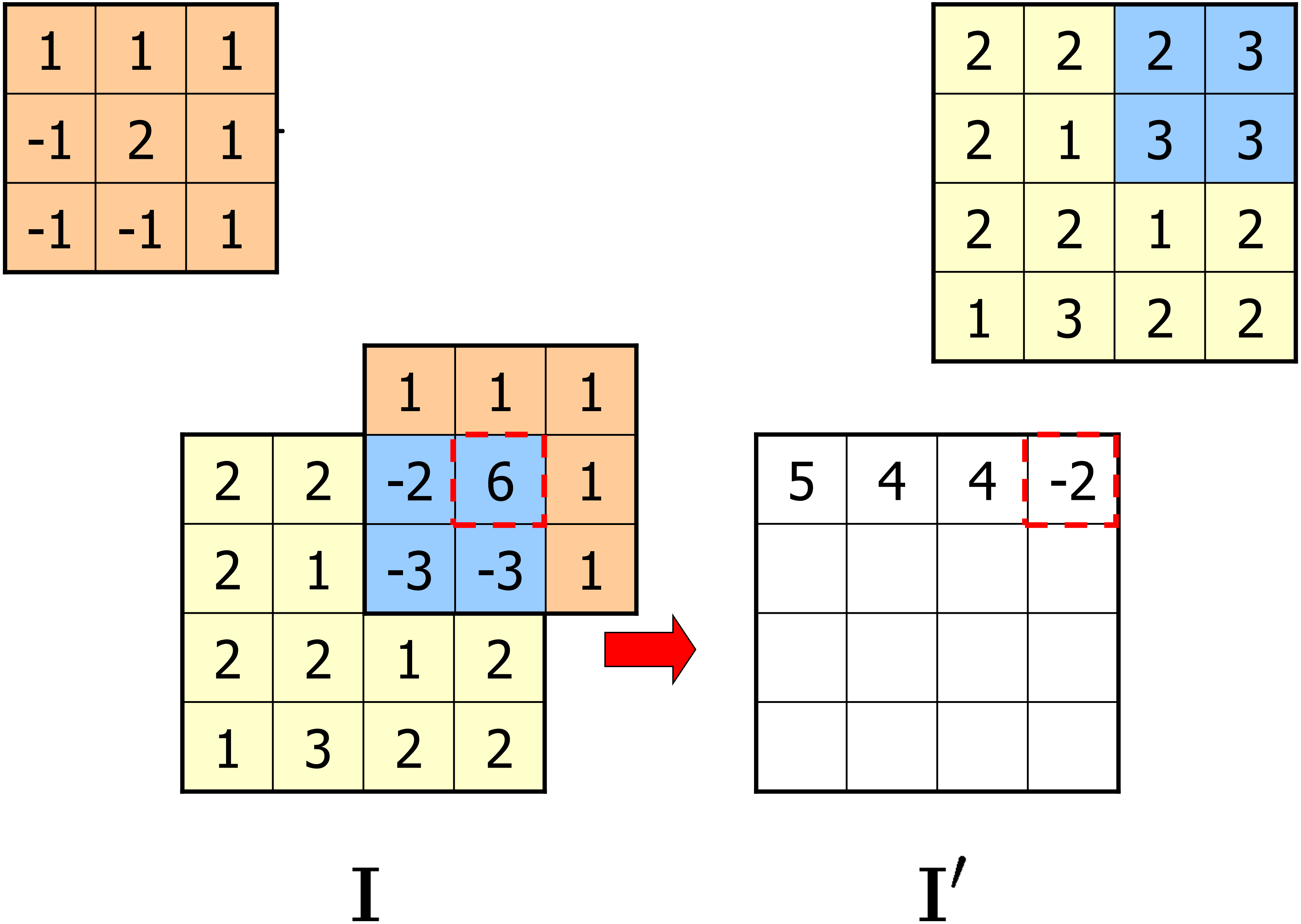
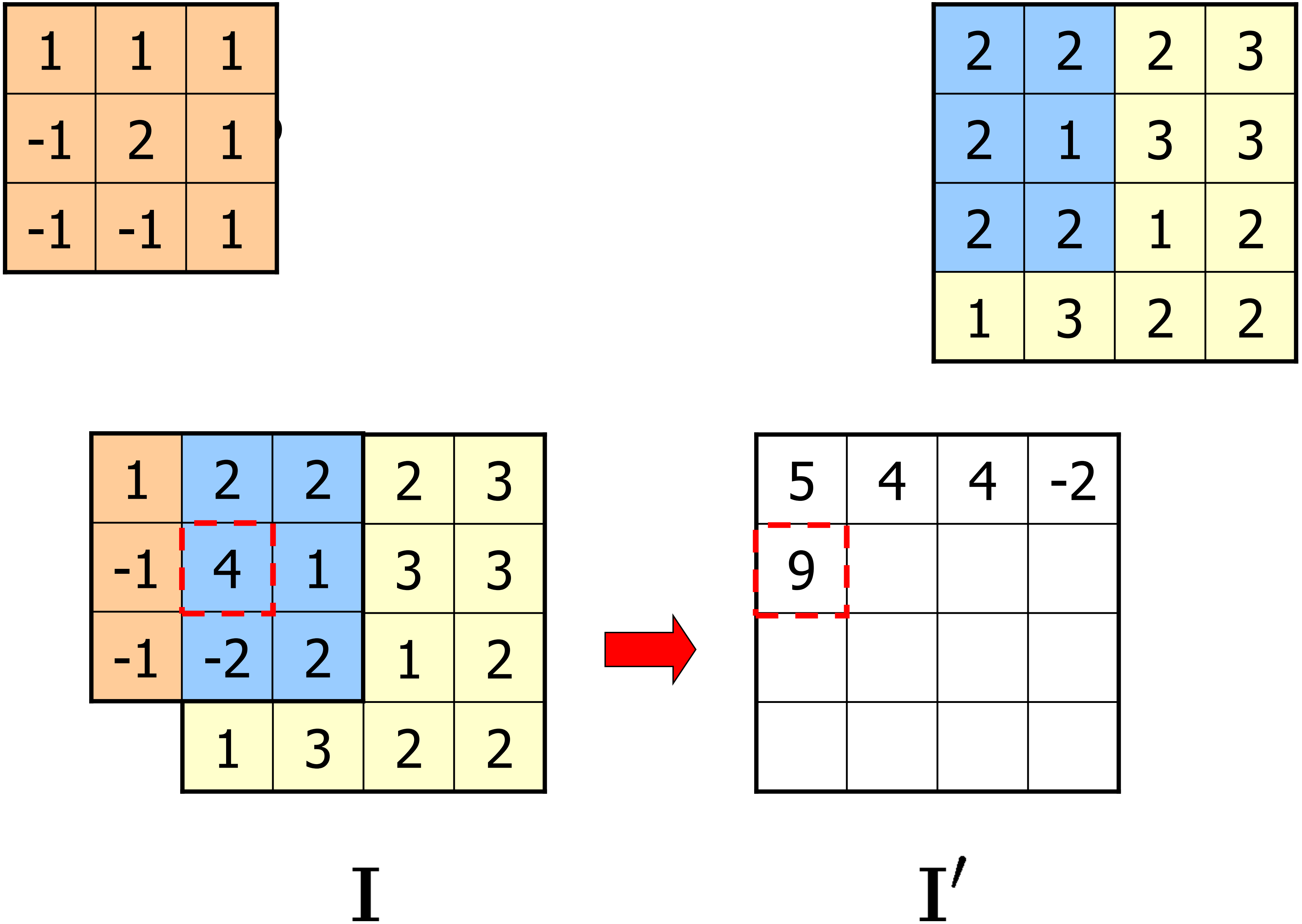


$\mathbf{I}$ $\mathbf{I}'$



1 1 1
-1 2 1
-1 -1 1
2 2 2 3
2 1 3 3
2 2 1 2
1 3 2 2
1 1 1
2 2 -2 6 1
2 1 -3 -3 1
2 2 1 2
1 3 2 2
5 4 4 -2
I
I′



I
I′

1	1	1
-1	2	1
-1	-1	1

2	2	2	3
2	1	3	3
2	2	1	2
1	3	2	2

2	2	2	3
-2	2	3	3
-2	-2	1	2
1	3	2	2

I

5	4	4	-2
9	6		

I′

Final Result

5	4	4	-2
9	6	14	5
11	7	6	5
9	12	8	5

$$\mathbf{I}'$$

Smoothing (Low-Pass) Filters

- Replace each pixel with average of neighbors
- Benefits: Suppress noise, aliasing
- Disadvantage: Sharp features blurred
- Types
  - Mean filter (box)
  - Median (nonlinear)
  - Gaussian

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

3 x 3 box filter

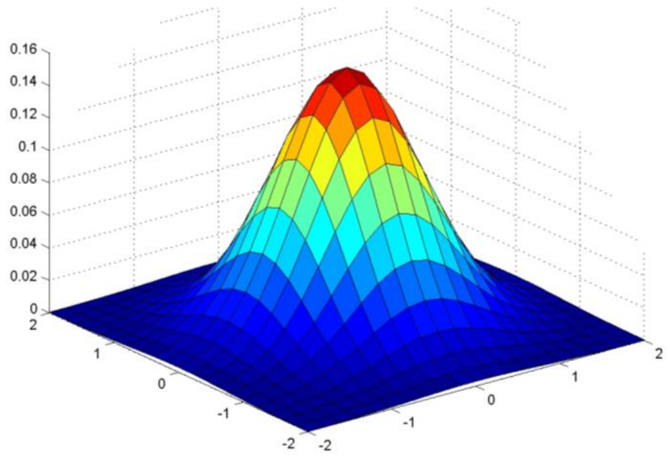
Box Filter: Smoothing

Original image

7 x 7 kernel

Gaussian Kernel

- Idea: Weight contributions of neighboring pixels by nearness



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

Gaussian: Smoothing

Original image

$\sigma = 1$

7 x 7 kernel

$\sigma = 3$

Gradient

- Think of image intensities as a function $\mathbf{I}(x, y.)$ Gradient of image is a vector field as for a normal 2-D height function:

$$\nabla \mathbf{I} = (\frac{\partial \mathbf{I}}{\partial x}, \frac{\partial \mathbf{I}}{\partial y})^T = (\mathbf{I}_x, \mathbf{I}_y)^T$$

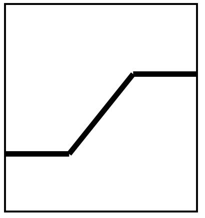
- **Edge**: Place where gradient magnitude is high; orthogonal to gradient direction

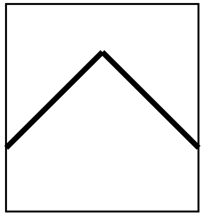
Edge Causes

- Depth discontinuity
- Surface orientation discontinuity
- Reflectance discontinuity (i.e., change in surface material properties)
- Illumination discontinuity (e.g., shadow)

Edge Detection

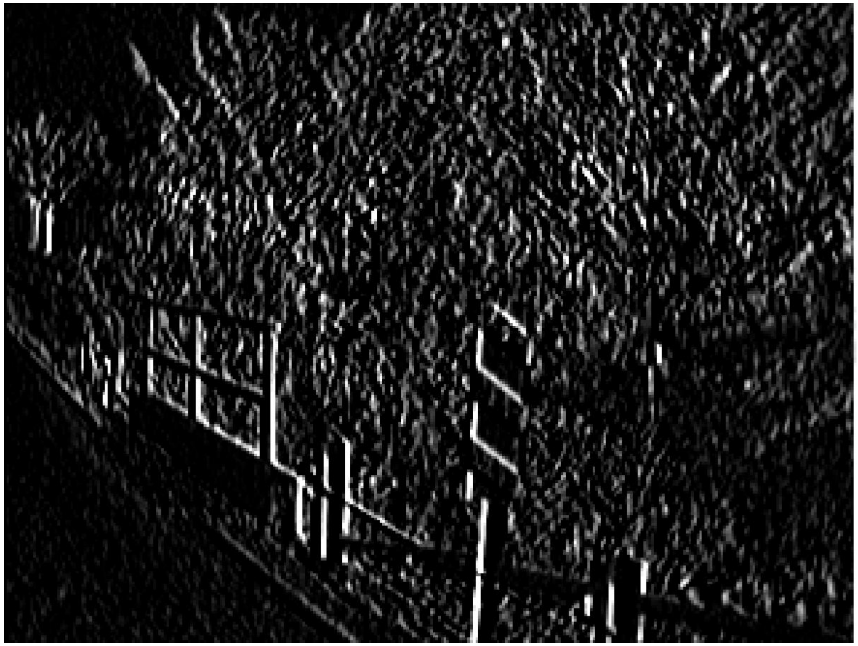
- Edge Types
  - Step edge (ramp)
  - Line edge (roof)



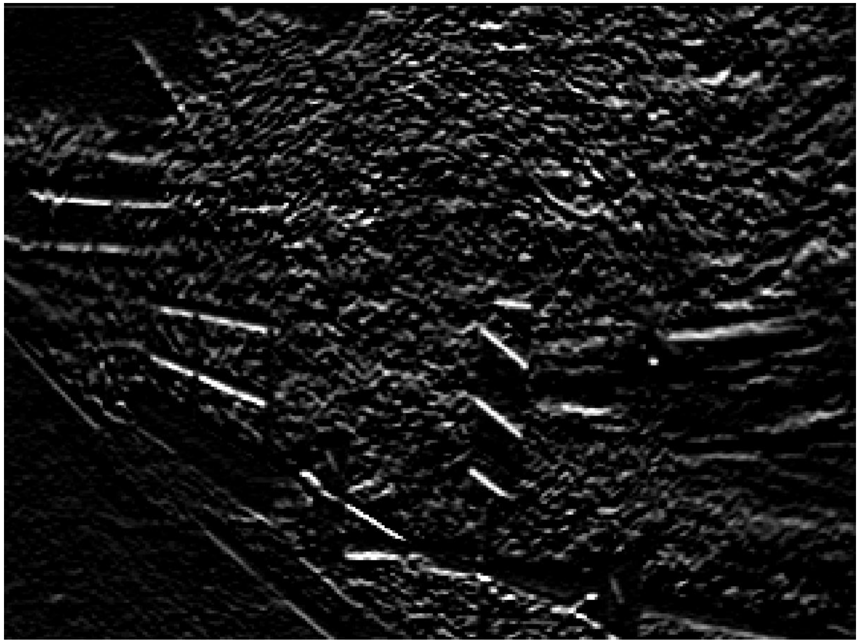


- Searching for Edges:
  - **Filter**: Smooth image
  - **Enhance**: Apply numerical derivative approximation
  - **Detect**: Threshold to find strong edges
  - **Localize/analyze**: Reject spurious edges, include weak but justified edges

Sobel Edge Detection: Gradient Approximation



Horizontal



Vertical

Sobel vs. LoG Edge Detection:

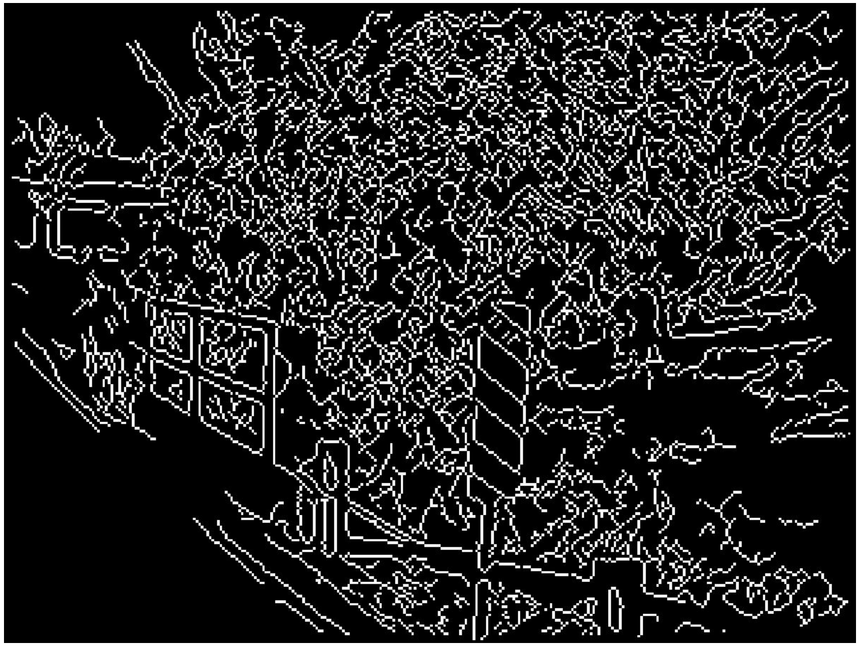
Sobel

LoG

Canny Edge Detection

- Derivative of Gaussian
- Non-maximum suppression
  - Thin multi-pixel wide “ridges” down to single pixel
- Thresholding
  - Low, high edge-strength thresholds
  - Accept all edges over low threshold that are connected to edge over high threshold

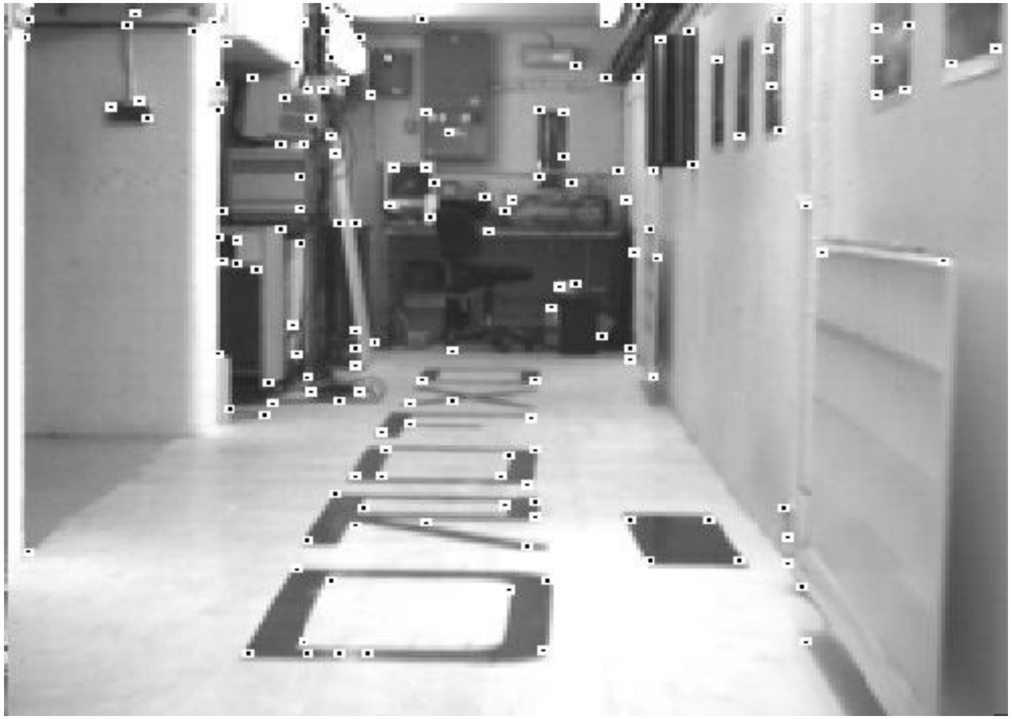
Canny Edge Detection: Example



(Matlab automatically set thresholds)

Corner Detection

- Basic idea: Find points where two edges meet—i.e., high gradient in orthogonal directions
- Harris corners (Harris & Stephens, 1988), Susan corners (Smith & Brady, 1997)



SUSAN corners

Outline

- Classification terminology
- Unsupervised learning (clustering)
- Supervised learning
  - *k*-Nearest neighbors
  - Linear discriminants
    - Perceptron, Relaxation, modern variants
  - Nonlinear discriminants
    - Neural networks, etc.
- Applications to computer vision
- Miscellaneous techniques

Classification Terms

- **Data**: A set of *N* vectors **x**
  - Features are parameters of **x**; **x** lives in *feature space*
  - May be whole, raw images; parts of images; filtered images; statistics of images; or something else entirely
- **Labels**: *C* categories; each **x** belongs to some c_i
- **Classifier**: Create formula(s) or rule(s) that will assign unlabeled data to correct category
  - Equivalent definition is to parametrize a *decision surface* in feature space separating category members

Key Classification Problems

- What features to use? How do we extract them from the image?
- Do we even have labels (i.e., examples from each category)?
- What do we know about the structure of the categories in feature space?

Unsupervised Learning

- May know number of categories *C*, but not labels
- If we don't know *C*, how to estimate?
  - Occam's razor (formalized as Minimum Description Length, or MDL, principle): Favor simpler classifiers over more complex ones
  - Akaike Information Criterion (AIC)
- Clustering methods
  - k-means
  - Hierarchical
  - Etc.

k-means Clustering

- Initialization: Given k categories, N points. Pick k points randomly; these are initial means $\mu_1, \ldots, \mu_k$
- (1) Classify N points according to nearest μ_i
- (2) Recompute mean μ_i of each cluster from member points
- (3) If any means have changed, goto (1)

Supervised Learning: Assessing Classifier Performance

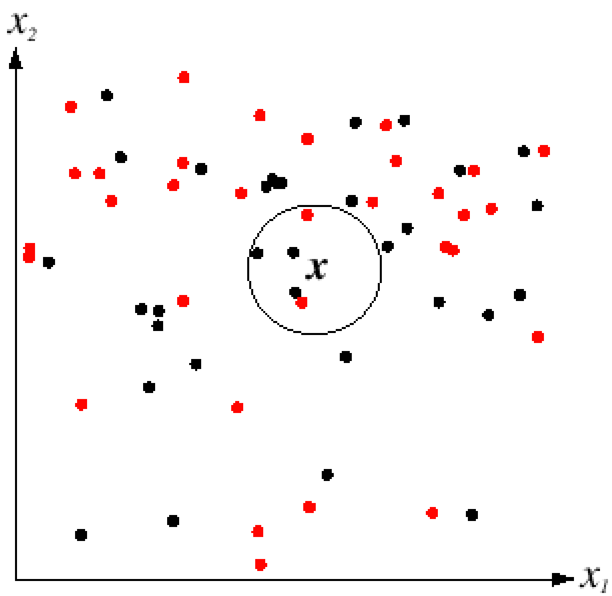
- Bias: Accuracy or quality of classification
- Variance: Precision or specificity—how stable is decision boundary for different data sets?
  - Related to generality of classification result $\rightarrow$ Overfitting to data at hand will often result in a very different boundary for new data

Supervised Learning: Procedures

- Validation: Split data into training and test set
  - Training set: Labeled data points used to guide parametrization of classifier
    - % misclassified guides learning
  - Test set: Labeled data points left out of training procedure
    - % misclassified taken to be overall classifier error
- *m*-fold Cross-validation
  - Randomly split data into *m* equal-sized subsets
  - Train *m* times on *m* - 1 subsets, test on left-out subset
  - Error is mean test error over left-out subsets
- Jackknife: Cross-validation with 1 data point left out
  - Very accurate; variance allows confidence measuring

k-Nearest Neighbor Classification

- For a new point, grow sphere in feature space until *k* labeled points are enclosed
- Labels of points in sphere vote to classify
- Low bias, high variance: No structure assumed



from
Duda et al.

Linear Discriminants

- Basic: $g(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + w_0$
  - $\mathbf{w}$ is weight vector, $\mathbf{x}$ is data, w_0 is bias or threshold weight
  - Number of categories
    - **Two**: Decide c_1 if $g(\mathbf{x}) < 0$, c_2 if $g(\mathbf{x}) > 0$. $g(\mathbf{x}) = 0$ is decision surface—a hyperplane when $g(\mathbf{x})$ linear
    - **Multiple**: Define C functions $g_i(\mathbf{x}) = \mathbf{w}^T \mathbf{x}_i + w_{i0}$. Decide c_i if $g_i(\mathbf{x}) > g_j(\mathbf{x})$ for all $j \neq i$
- Generalized: $g(\mathbf{x}) = \mathbf{a}^T \mathbf{y}$
  - Augmented form: $\mathbf{y} = (1, \mathbf{x}^T)^T$, $\mathbf{a} = (w_0, \mathbf{w}^T)^T$
  - Functions $\mathbf{y}_i = y_i(\mathbf{x})$ can be nonlinear—e.g., $\mathbf{y} = (1, x, x^2)^T$

Dimensionality Reduction

- Functions $\mathbf{y}_i = y_i(\mathbf{x})$ can reduce dimensionality of feature space $\rightarrow$ More efficient classification
- If chosen intelligently, we won't lose much information and classification is easier
- Common methods
  - Principal components analysis (PCA): Maximize total "scatter" of data

    $$S_T = \sum_{k=1}^{N} (x_k - \mu)(x_k - \mu)^T$$

  - Fisher's Linear Discriminant (FLD): Maximize ratio of between-class scatter to within-class scatter

Principal Component Analysis

- Orthogonalize feature vectors so that they are uncorrelated
- Inverse of this transformation takes zero mean, unit variance Gaussian to one describing covariance of data points
- Distance in transformed space is *Mahalanobis distance*
- By dropping eigenvectors of covariance matrix with low eigenvalues, we are essentially throwing away least important dimensions

PCA

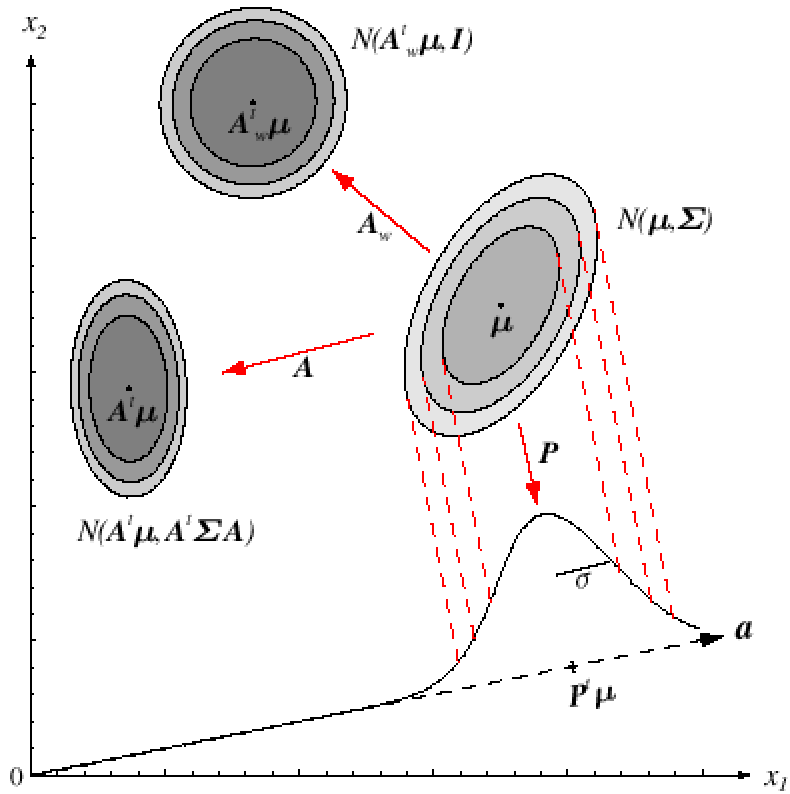


FIGURE 2.8. The action of a linear transformation on the feature space will convert an arbitrary normal distribution into another normal distribution. One transformation, $\mathbf{A}$, takes the source distribution into distribution $N(\mathbf{A}^t\boldsymbol{\mu}, \mathbf{A}^t\boldsymbol{\Sigma}\mathbf{A})$. Another linear transformation—a projection $\mathbf{P}$ onto a line defined by vector $\mathbf{a}$—leads to $N(\mu, \sigma^2)$ measured along that line. While the transforms yield distributions in a different space, we show them superimposed on the original x_1x_2-space. A whitening transform, $\mathbf{A}_w$, leads to a circularly symmetric Gaussian, here shown displaced. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Face Recognition (Belhumeur et al., 1996)

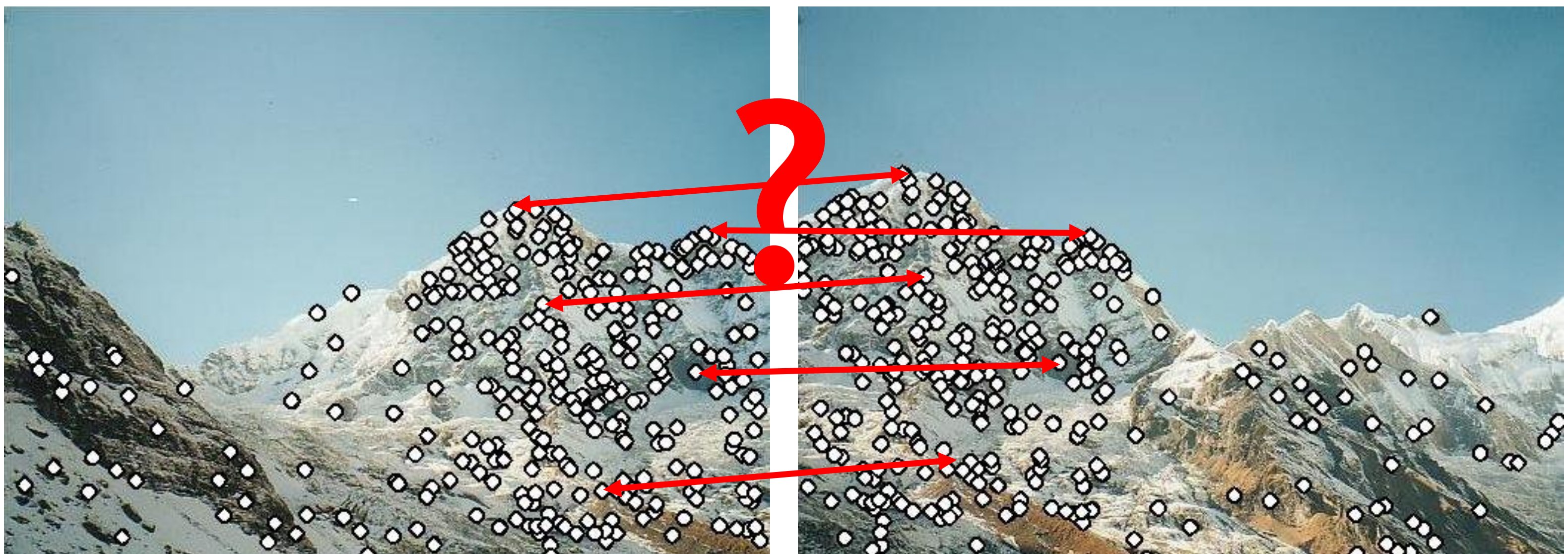
- Given cropped images {**I**} of faces with different lighting, expressions

- Nearest neighbor approach equivalent to correlation (**I**'s normalized to 0 mean, variance 1)
  - Lots of computation, storage
- PCA projection ("Eigenfaces")
  - Better, but sensitive to variation in lighting conditions
- FLD projection ("Fisherfaces")
  - Best (for this problem)

Local Descriptors

- We know how to detect points
- Next question:

How to *describe* them for matching?

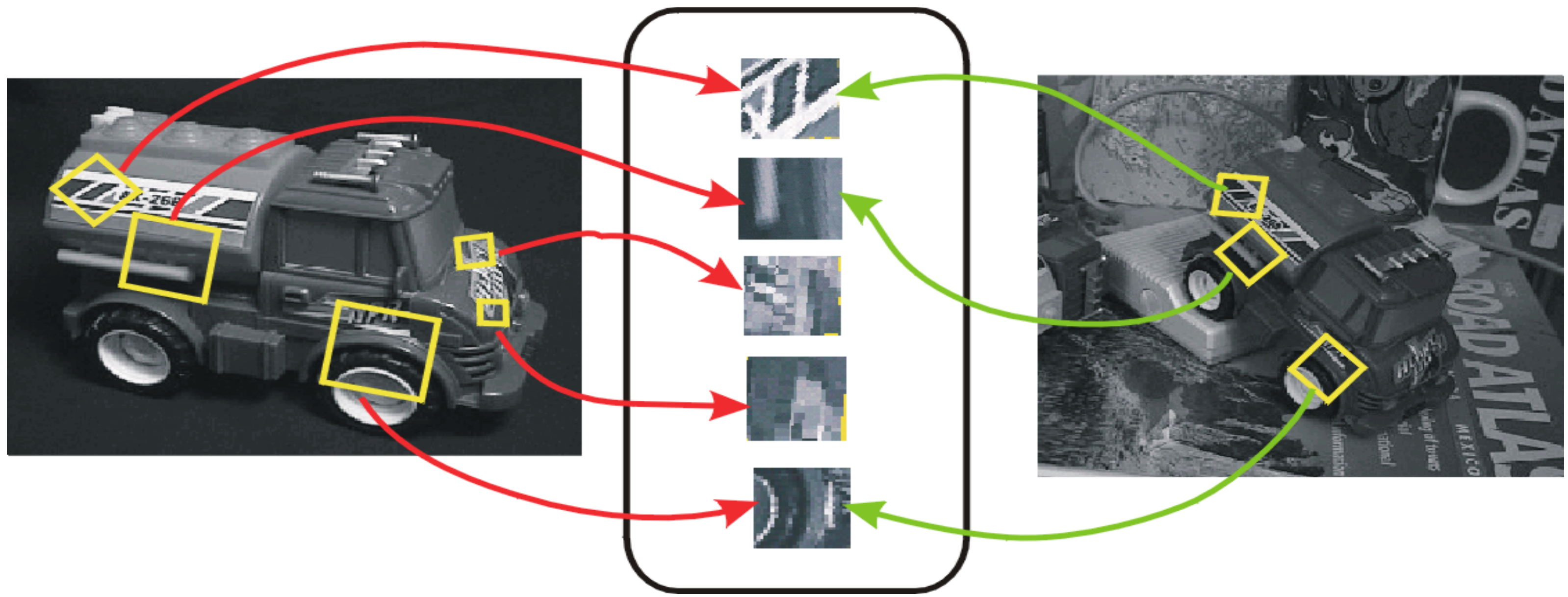


Point descriptor should be:
1. **Invariant**
2. **Distinctive**

Slide credit: Kristen Grauman

Invariant Local Features

- Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters

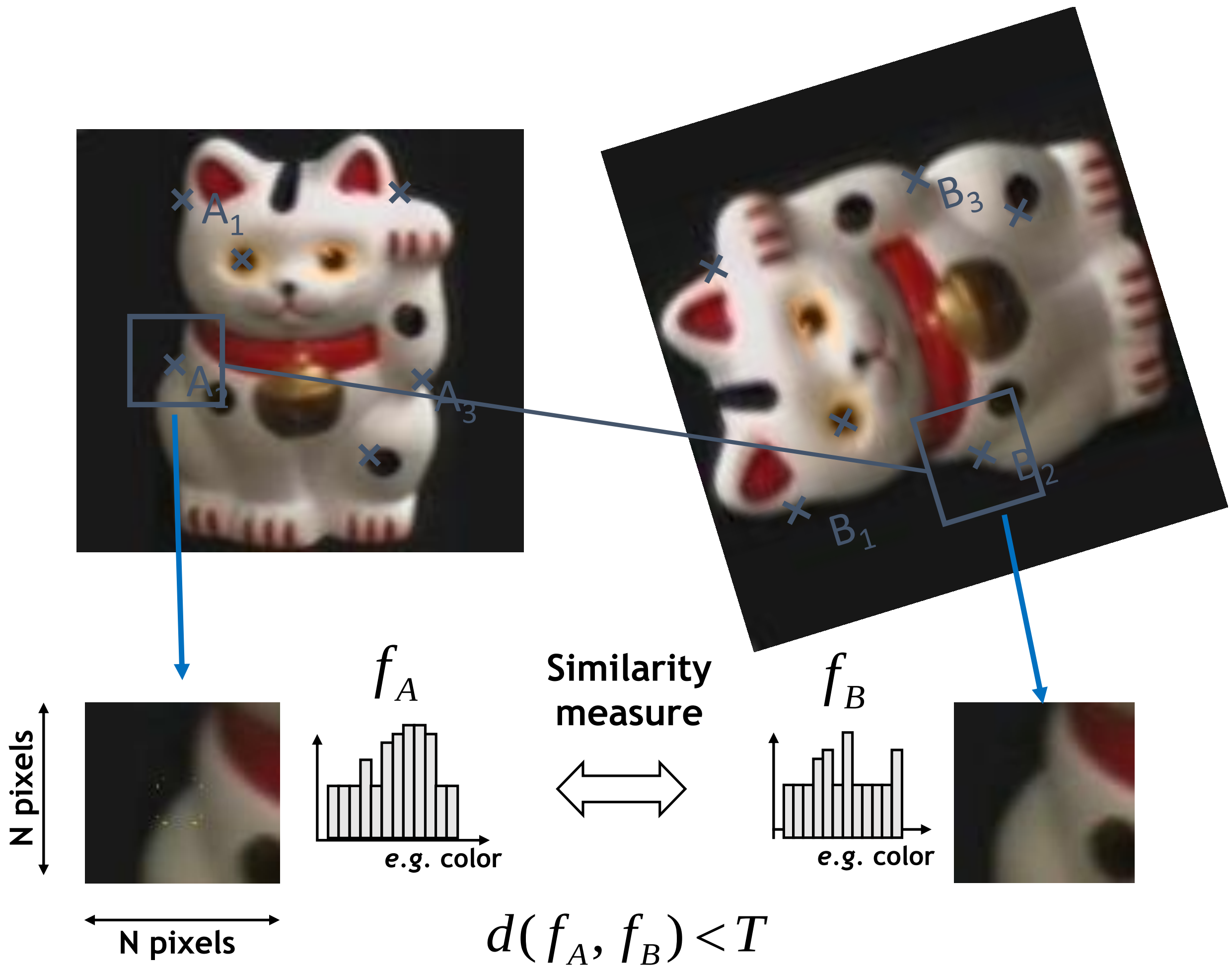


Following slides credit: CVPR 2003 Tutorial on **Recognition and Matching Based on Local Invariant Features** David Lowe

Advantages of invariant local features

- **Locality:** features are local, so robust to occlusion and clutter (no prior segmentation)
- **Distinctiveness:** individual features can be matched to a large database of objects
- **Quantity:** many features can be generated for even small objects
- **Efficiency:** close to real-time performance
- **Extensibility:** can easily be extended to wide range of differing feature types, with each adding robustness

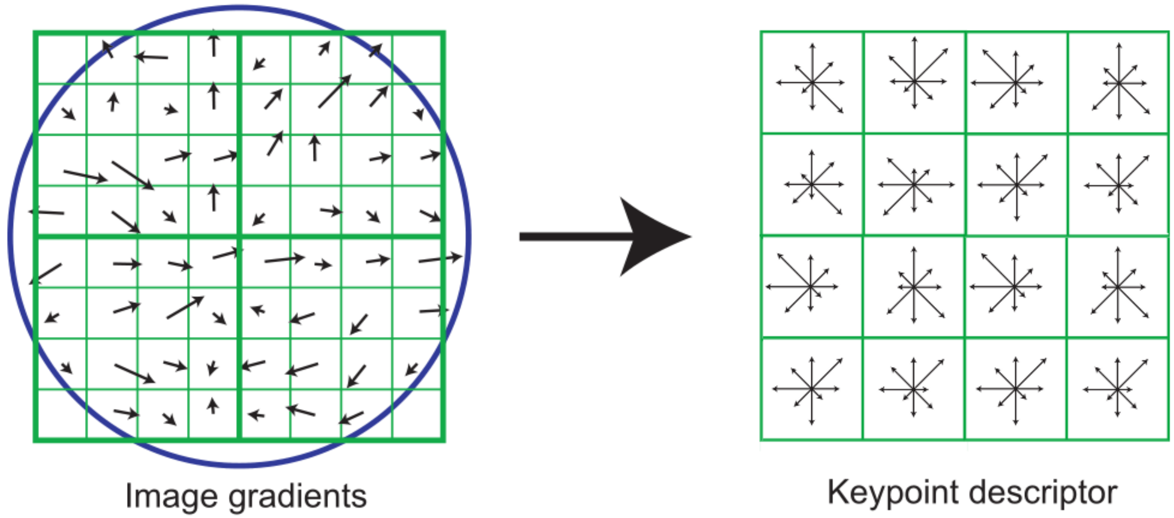
Features Detector: General Approach



1. Find a set of distinctive key-points
2. Define a region around each keypoint
3. Extract and normalize the region content
4. Compute a local descriptor from the normalized region
5. Match local descriptors

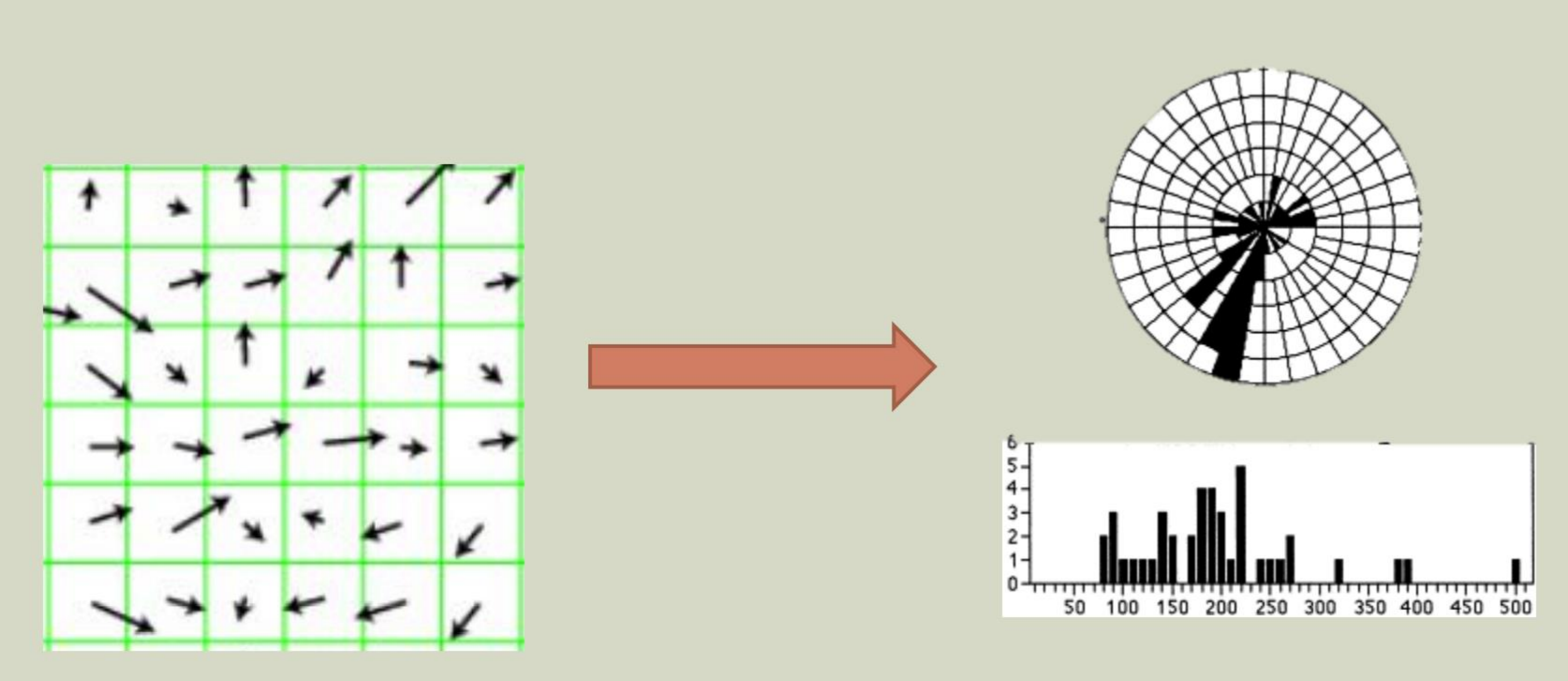
Slide credit: Bastian Leibe

SIFT descriptor formation

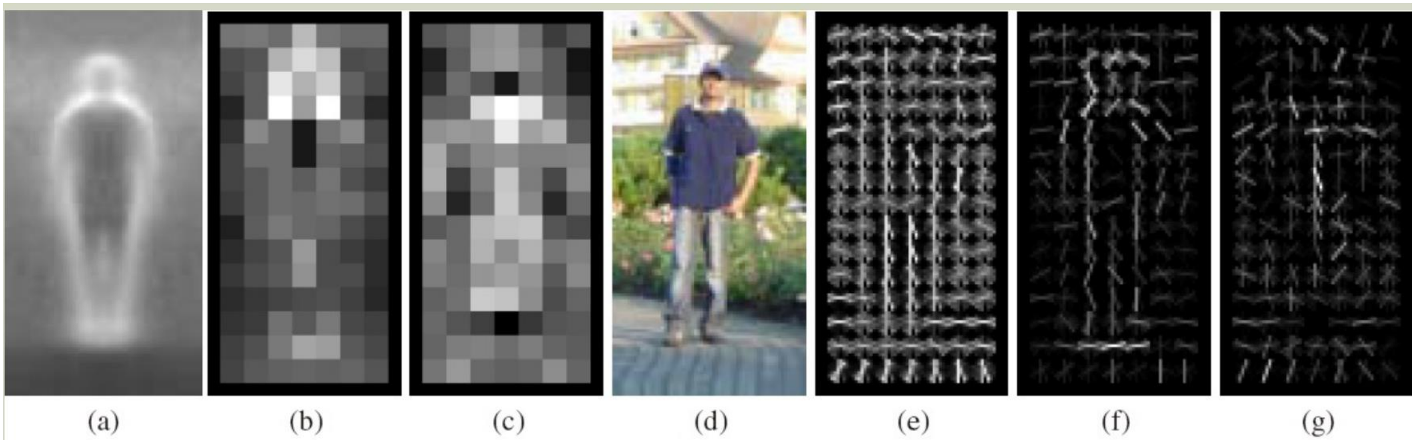


- Using precise gradient locations is fragile. We'd like to allow some "slop" in the image, and still produce a very similar descriptor
- Create array of orientation histograms (a 4x4 array is shown)
- Put the rotated gradients into their local orientation histograms
    - A gradients's contribution is divided among the nearby histograms based on distance. If it's halfway between two histogram locations, it gives a half contribution to both.
    - Also, scale down gradient contributions for gradients far from the center
- The SIFT authors found that best results were with 8 orientation bins per histogram, and a 4x4 histogram array.

Histogram of Oriented Gradients



Visualizing HoG



a. Average gradient over positive examples
b. Maximum positive weight in each block
c. Maximum negative weight in each block
d. A test image
e. It's R-HOG descriptor
f. R-HOG descriptor weighted by positive weights
g. R-HOG descriptor weighted by negative weights

A simple pipeline - Training