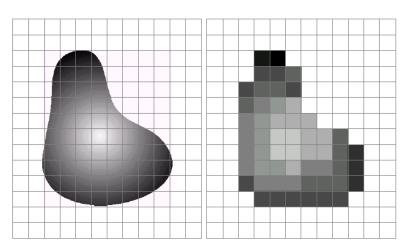
Features

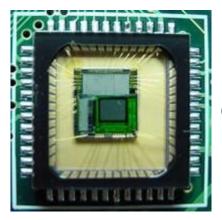
CMP719- Computer Vision
Pinar Duygulu
Hacettepe University

Digital Color Images

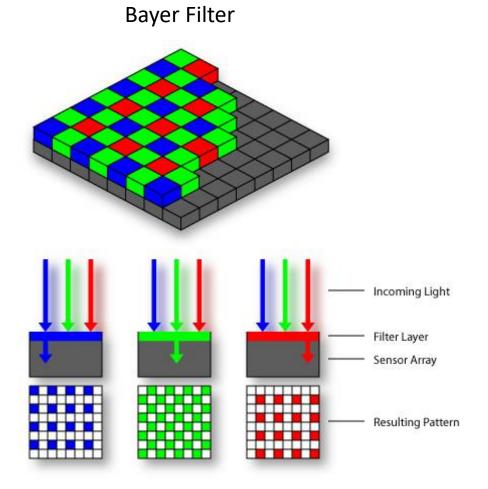


a 1

FIGURE 2.17 (a) Continuos image projected onto a sensor array. (b) Result of image sampling and quantization.



CMOS sensor



Color Image

R



Images in Matlab Images represented as a matrix

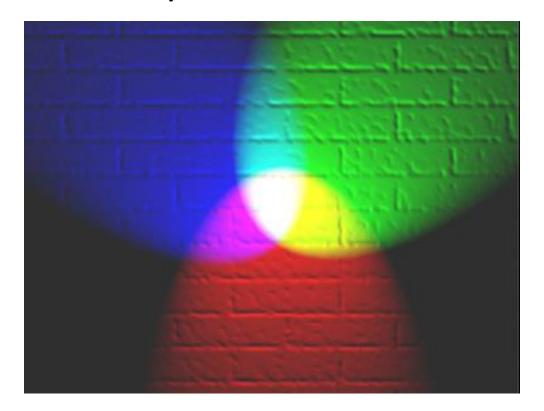
- Suppose we have a NxM RGB image called "im"
 - im(1,1,1) = top-left pixel value in R-channel
 - im(y, x, b) = y pixels down, x pixels to right in the bth channel
 - im(N, M, 3) = bottom-right pixel in B-channel
- imread(filename) returns a uint8 image (values 0 to 255)
 - Convert to double format (values 0 to 1) with im2double

row	column											R				
	0.92	0.93	0.94	0.97	0.62	0.37	0.85	0.97	0.93	0.92	0.99	''				
	0.95	0.89	0.82	0.89	0.56	0.31	0.75	0.92	0.81	0.95	0.91			_		
	0.89	0.72	0.51	0.55	0.51	0.42	0.57	0.41	0.49	0.91	0.92	0.92	0.99	1 G		
	0.96	0.95	0.88	0.94	0.56	0.46	0.91	0.87	0.90	0.97	0.95	0.95	0.91			В
	0.71	0.81	0.81	0.87	0.57	0.37	0.80	0.88	0.89	0.79	0.85	0.91 0.92	<u> </u>		В	
	0.49	0.62	0.60	0.58	0.50	0.60	0.58	0.50	0.61	0.45	0.33	0.97	0.95	0.92	0.99	
	0.86	0.84	0.74	0.58	0.51	0.39	0.73	0.92	0.91	0.49	0.74	0.79	0.85	0.95	0.91	
	0.96	0.67	0.54	0.85	0.48	0.37	0.88	0.90	0.94	0.82	0.93	0.45	0.33	0.91	0.92	
	0.69	0.49	0.56	0.66	0.43	0.42	0.77	0.73	0.71	0.90	0.99	0.49	0.74	0.97	0.95	
	0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97	0.82	0.93	0.79	0.85	
W	0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93	0.90 0.99		0.45	0.33	
			0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97	0.49	0.74	
0.91 0.94					0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93	0.82	0.93	
0.31 0.31					0.05	0.43	0.50	0.78	0.78	0.77	0.83	0.75	0.73	0.90	0.99	
					0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97	
t: Derek Hoiem					0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93	

Slide credit

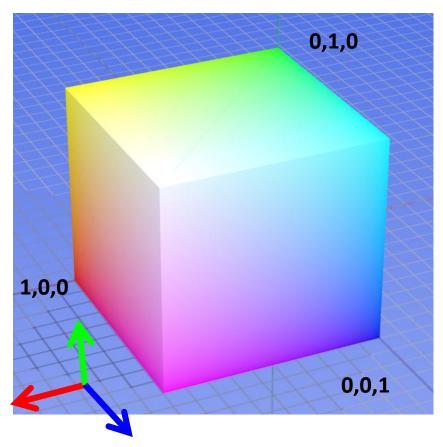
Color spaces

How can we represent color?











R (G=0,B=0)



G (R=0,B=0)



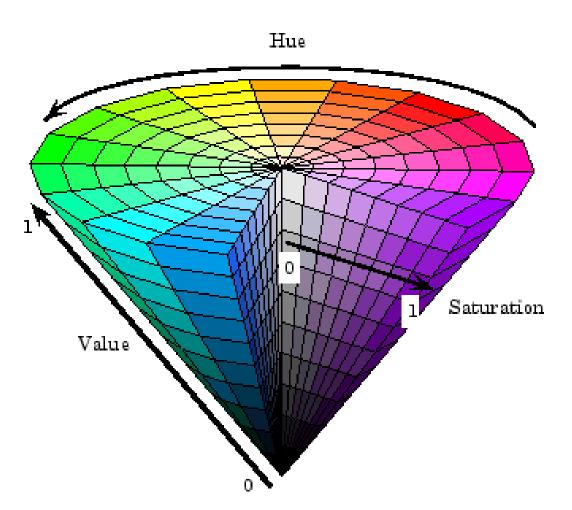
B (R=0,G=0)

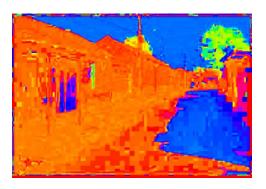
Some drawbacks

- Strongly correlated channels
- Non-perceptual



Intuitive color space





H (S=1,V=1)

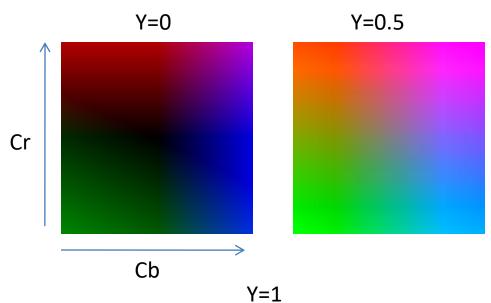


S (H=1,V=1)



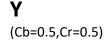
V (H=1,S=0)

Fast to compute, good for paces: YCbCr compression, used by TV



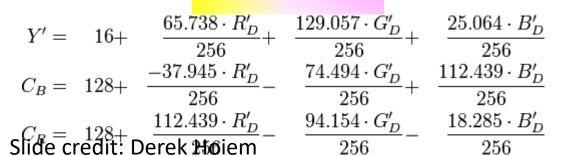








Cb (Y=0.5,Cr=0.5)

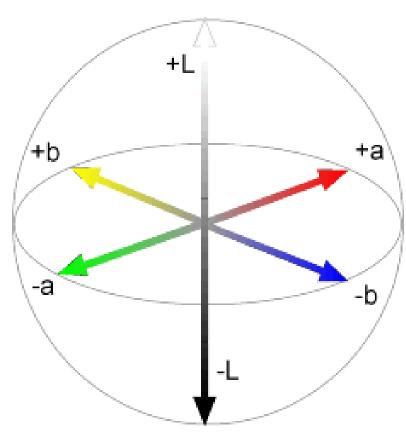




Cr (Y=0.5,Cb=05)

Color spaces: CIE L*a*b* "Perceptually uniform" color space

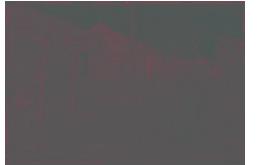




Luminance = brightness Slide credit: Derek Holem



(a=0,b=0)



(L=65,b=0)



(L=65,a=0)

Which contains more information?

(a) **intensity** (1 channel)

(b) **chrominance** (2 channels)

Most information in intensity



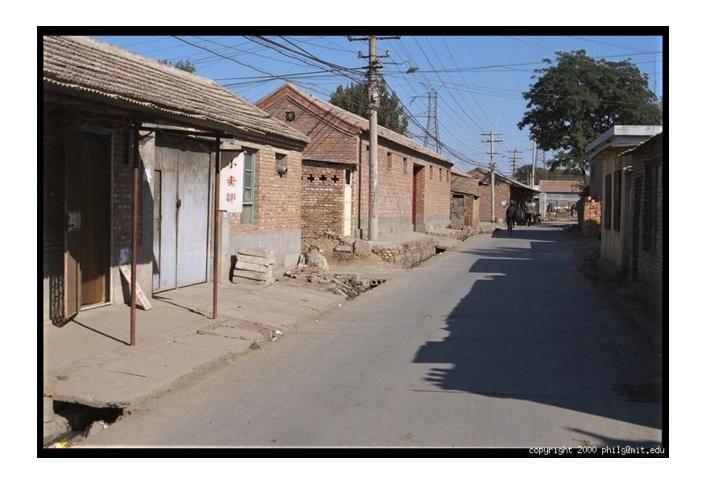
Only color shown – constant intensity

Most information in intensity



Only intensity shown – constant color

Most information in intensity



Original image

Development of Low-Level Image Features

1999

Classical features

- Raw pixel
- Histogram feature
 - Color histogram
 - Edge histogram
- Frequency analysis
- Image filters
- Texture features
 - LBP
- Scene features
 - GIST
- Shape descriptors
- Edge detection
- Corner detection

SIFT

Local Descriptors

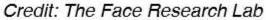
- HOG
- SURF
- DAISY
- BRIEF
- ...
- DoG

Local Detectors

- Hessian detector
- Laplacian of Harris
- FAST
- ORB
- ...

Concatenating Raw Pixels As 1D Vector





Concatenated Raw Pixels

Famous applications (widely used in ML field)

Face recognition



Hand-written digits

Tiny Images

Antonio Torralba et al. proposed to resize images to 32x32 color thumbnails, which are called "tiny images"









office

waiting area

dining room

dining room

- Related applications
 - Scene recognition
 - Object recognition

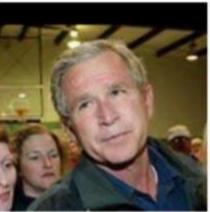
Fast speed with limited accuracy

Problem of raw-pixel based representation

- Rely heavily on good alignment
- Assume the images are of similar scale
- Suffer from occlusion
- Recognition from different view point will be difficult

We want more powerful features for real-world problems like the following







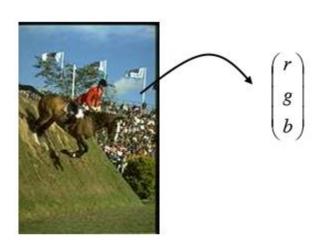


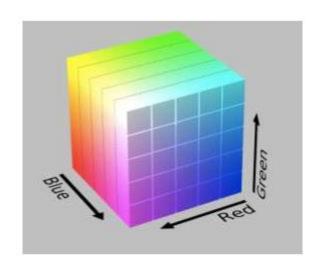
Slide credit: Liangliang Cao

Color Histogram

Each pixel is described by a vector of pixel values

Distribution of color vectors is described by a histogram

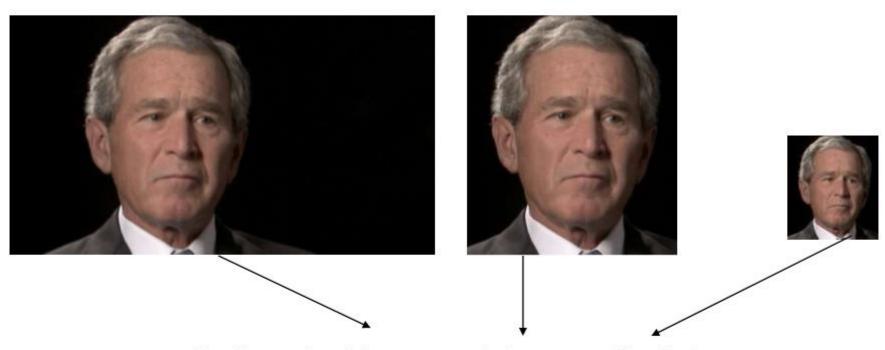




Note: There are different choices for color space: RGB, HSV, Lab, etc. For gray images, we usually use 256 or fewer bins for histogram.

Benefits of Histogram Representations

No longer sensitive to alignment, scale transform, or even global rotation

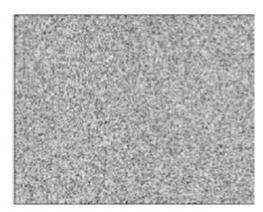


Similar color histograms (after normalization)

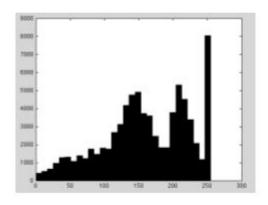
Limitation of Global Histogram

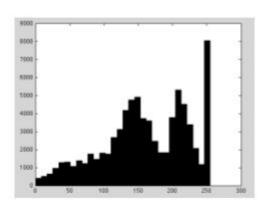
Global histogram has no location information at all





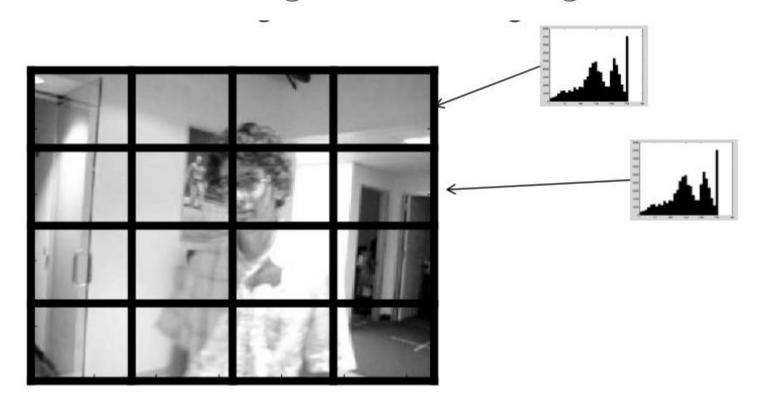
They're equal in terms of global histogram





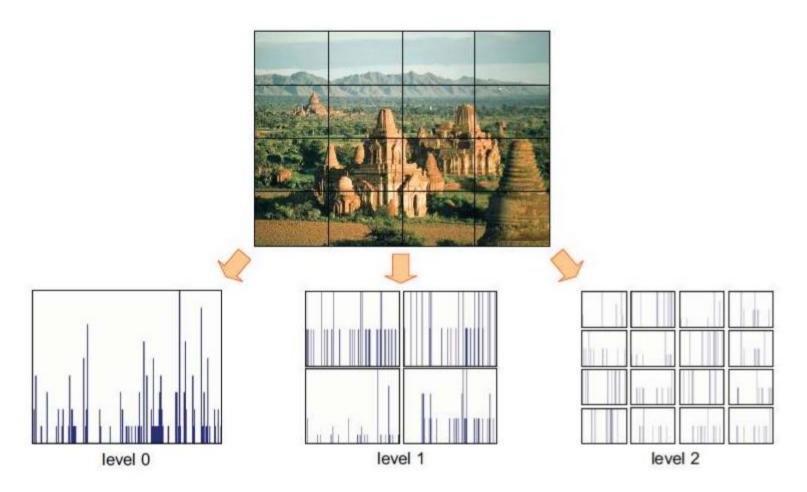
Histogram with Spatial Layout

Concatenated histogram for each region



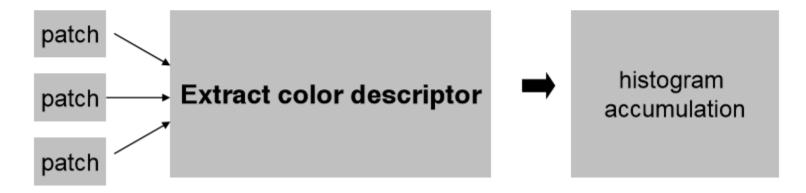
Spatial Pyramid Matching

• Lazebnik, Schmid and Ponce, CVPR'06



General Histogram Representation

Color histogram

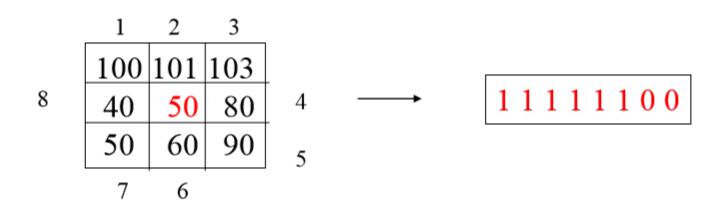


General histogram



Local Binary Pattern (LBP)

- For each pixel p, create an 8-bit number b₁ b₂ b₃ b₄ b₅ b₆ b₇ b₈, where b_i = 0 if neighbor i has value less than or equal to p's value and 1 otherwise.
- Represent the texture in the image (or a region) by the histogram of these numbers.



LBP Histogram

- Divide the examined window to cells (e.g. 16x16 pixels for each cell).
- Compute the histogram, over the cell, of the frequency of each "number" occurring.
- Optionally normalize the histogram.
- Concatenate normalized histograms of all cells.

