

Image Processing

Empirical Evaluation of Dissimilarity
Measures for Color and Texture
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Image processing

Image processing

Computer vision

Computer Graphics

Text retrieval

What was the key problem we needed to solve for text retrieval?

$$\text{sim}\left(\begin{array}{c} \text{query} \\ \text{document} \end{array}\right) = ?$$

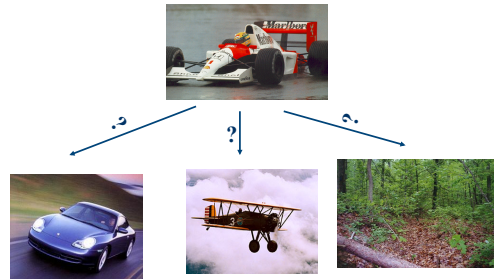
The Problem: Image Similarity

$$\text{sim}\left(\begin{array}{c} \text{Homer Simpson} \\ \text{Duke the dog} \end{array}\right) = ?$$

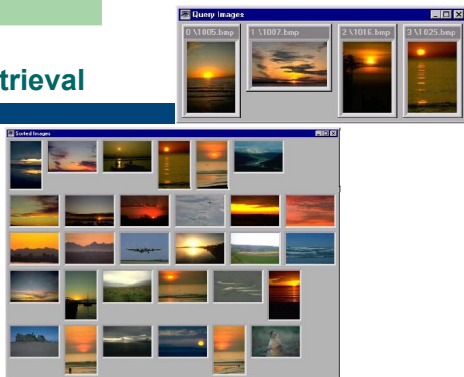
Where does this problem arise in computer vision?

- Image Classification
- Image Retrieval
- Image Segmentation

Classification

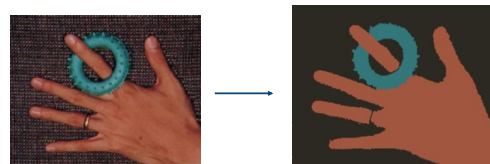


Retrieval



Jeremy S. De Bonet, Paul Viola (1997). Structure Driven Image Database Retrieval. Neural Information Processing 10 (1997).

Segmentation

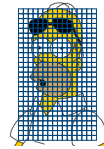


http://vizlab.rutgers.edu/~comanici/segm_images.html

How is an image represented?



How is an image represented?

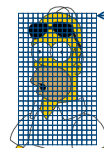


- images are made up of pixels
- for a color image, each pixel corresponds to an RGB value (i.e. three numbers)

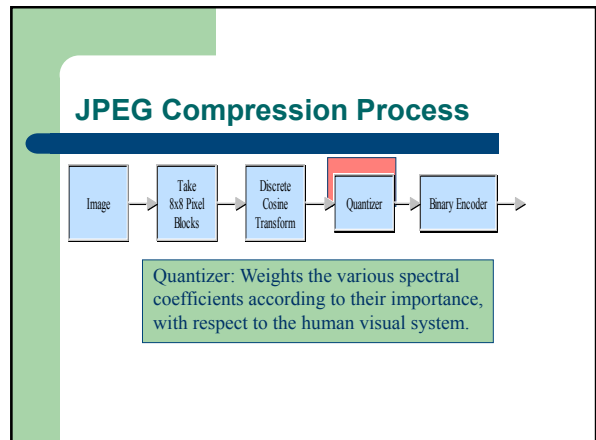
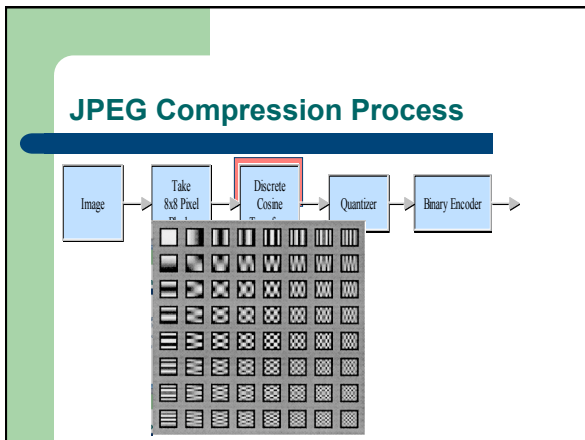
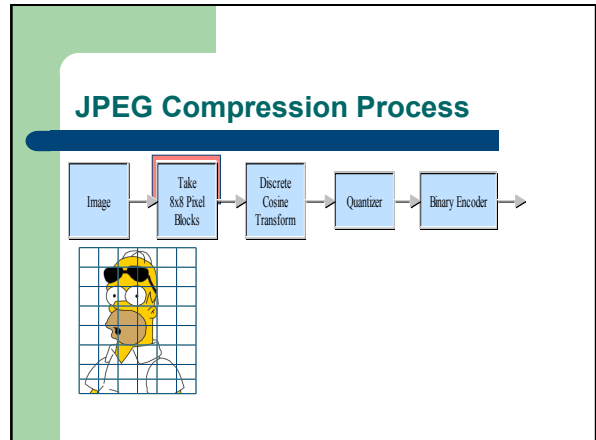
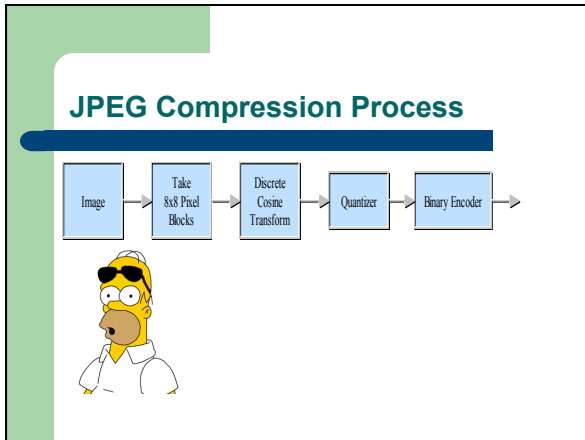
Image file formats

- BitMaP
- JPEG
- TIFF
- Gif
- Png
-

Bitmap



R, G, B



JPEG Compression

JPEG Image with a Lossy Compression Ratio of 10

JPEG Image with a Lossy Compression Ratio of 10

JPEG Image with a Lossy Compression Ratio of 20

Image features

?

Color

Which is more similar?

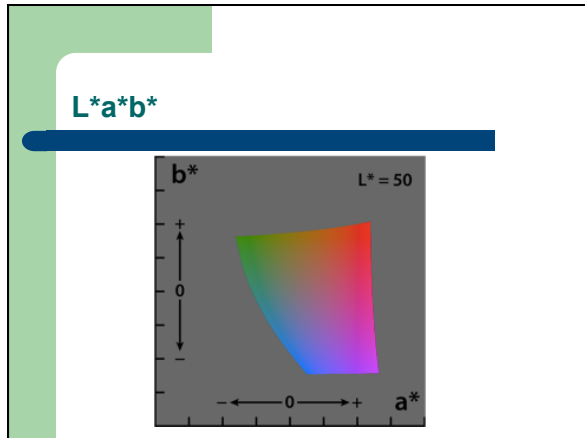
L*a*b* was designed to be uniform in that perceptual "closeness" corresponds to Euclidean distance in the space.

L*a*b*

L – lightness (white to black)

a – red-greenness

b – yellowness-blueness



Texture

How is texture different than color?

Texture

Texture is not pointwise like color

Texture involves a local neighborhood

How can we capture texture?
How did we capture audio texture?

Gabor Filters


Gabor filters are Gaussians modulated by sinusoids

They can be tuned in both the scale (size) and the orientation

A filter is applied to a region and is characterized by some feature of the energy distribution (often mean and standard deviation)

Similar idea to wavelets (Gabor wavelet)!

Examples of Gabor Filters




Scale: 3 at 72° Scale: 4 at 108° Scale: 5 at 144°

Gabor filters

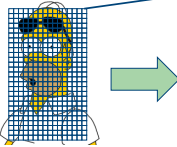


What would the response look like to a vertical filter?

Gabor filters



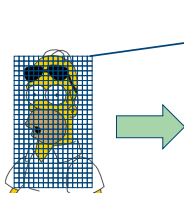
Features



- set of color features
- set of texture features (i.e. responses to different filters)
- ...

any problem?

Features



For each pixel:

- set of color features
- set of texture features (i.e. responses to different filters)
- ...

- Lots of features!
- Extremely sparse
- Features are position dependent

Ideas?

One approach: histograms

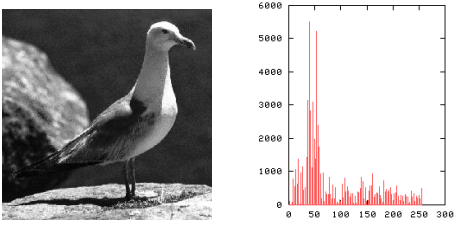
Examine the distribution of features, rather than the features themselves

General purpose (i.e. any distribution of features)

Resilient to variations (shading, changes in illumination, shading, etc.)

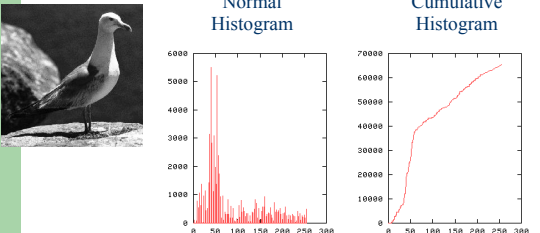
Can use previous work in statistics, etc.

Histogram Example



The histogram shows the frequency of pixel intensities. The x-axis represents intensity from 0 to 300, and the y-axis represents frequency from 0 to 6000. The distribution is highly peaked around an intensity of 50, indicating a high concentration of light pixels.

Cumulative Histogram



The normal histogram shows the frequency of pixel intensities, with a peak around 50. The cumulative histogram shows the cumulative frequency of pixel intensities, with a curve that rises steeply at low intensities and levels off as intensity increases.

Similarity Measures Using the Histograms

Histogram 1

Histogram 2

Need to quantify how similar two histograms are

Heuristic Histogram Distances

Minkowski-form distance L_p

$$D(I, J) = \left(\sum_i |I_i - J_i|^p \right)^{1/p}$$

Special cases:

- L_1 : absolute, cityblock, or Manhattan distance
- L_2 : Euclidian distance
- L_∞ : Maximum value distance

More heuristic distances

Weighted-Mean-Variance (WMV)

$$D^r(I, J) = \frac{|\mu_r(I) - \mu_r(J)|}{|\sigma(\mu_r)|} + \frac{|\sigma_r(I) - \sigma_r(J)|}{|\sigma(\sigma_r)|}$$

- Only includes minimal information about distribution

Cumulative Difference Example

Histogram 1

Histogram 2

Difference

$L_\infty =$

$L_2 =$

How would you test the performance of these algorithms?

Three tasks

- classification
- retrieval
- segmentation

Data Set: Color

Randomly chose 94 images from set of 2000

- 94 images represent separate classes

Randomly select disjoint set of pixels from the images

- Set size of 4, 8, 16, 32, 64 pixels
- 16 disjoint samples per set per image

Data Set: Texture

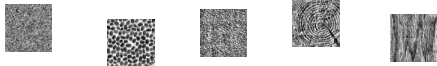
Brodatz album

- Collection of wide range of texture (e.g. cork, lawn, straw, pebbles, sand, etc.)

Each image is considered a class (as in color)

Extract sets of 16 non-overlapping blocks

- sizes 8x8, 16x16, ..., 256x256



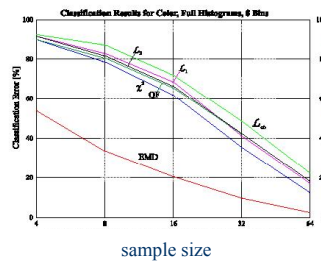
Setup: Classification

How can we use similarity for classification?

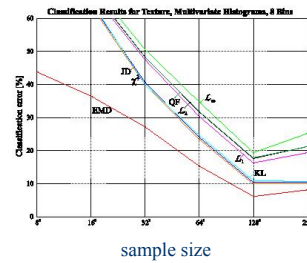
k-Nearest Neighbor classifier is used

- Nearest Neighbor classification: given a collection of labeled points S and a query point q , what point belonging to S is closest to q ?
- k nearest is a majority vote of the k closest points

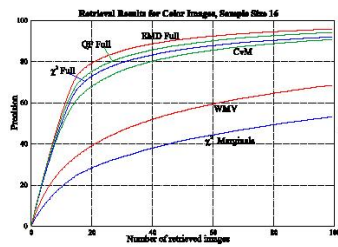
Results: Classification, color data set



Results: Classification, texture data set



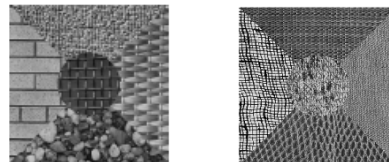
Results: Image Retrieval



Setup: Segmentation

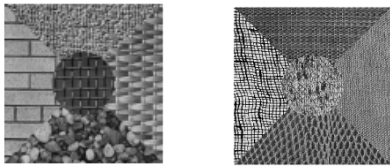
100 images

Each image consists of 5 different textures



Setup: Segmentation

How can we solve this problem using our similarity measures?



Setup: Segmentation (cont.)

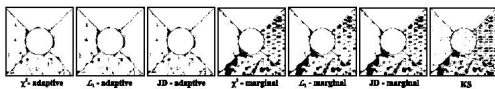
Image is divided into 16384 sites (128 x 128 grid)

A histogram is calculate for each site

Each site histogram is then compared with 80 randomly selected sites

Image sites with high average similarity are then grouped

Results: Segmentation



Something fun...

- <http://www.popsci.com/gear-amp-gadgets/article/2009-09/building-virtual-cities-automatically-150000-flickr-photos>