

VK Multimedia Information Systems

Mathias Lux, mlux@itec.uni-klu.ac.at
Dienstags, 16.00 Uhr c.t., E.1.42

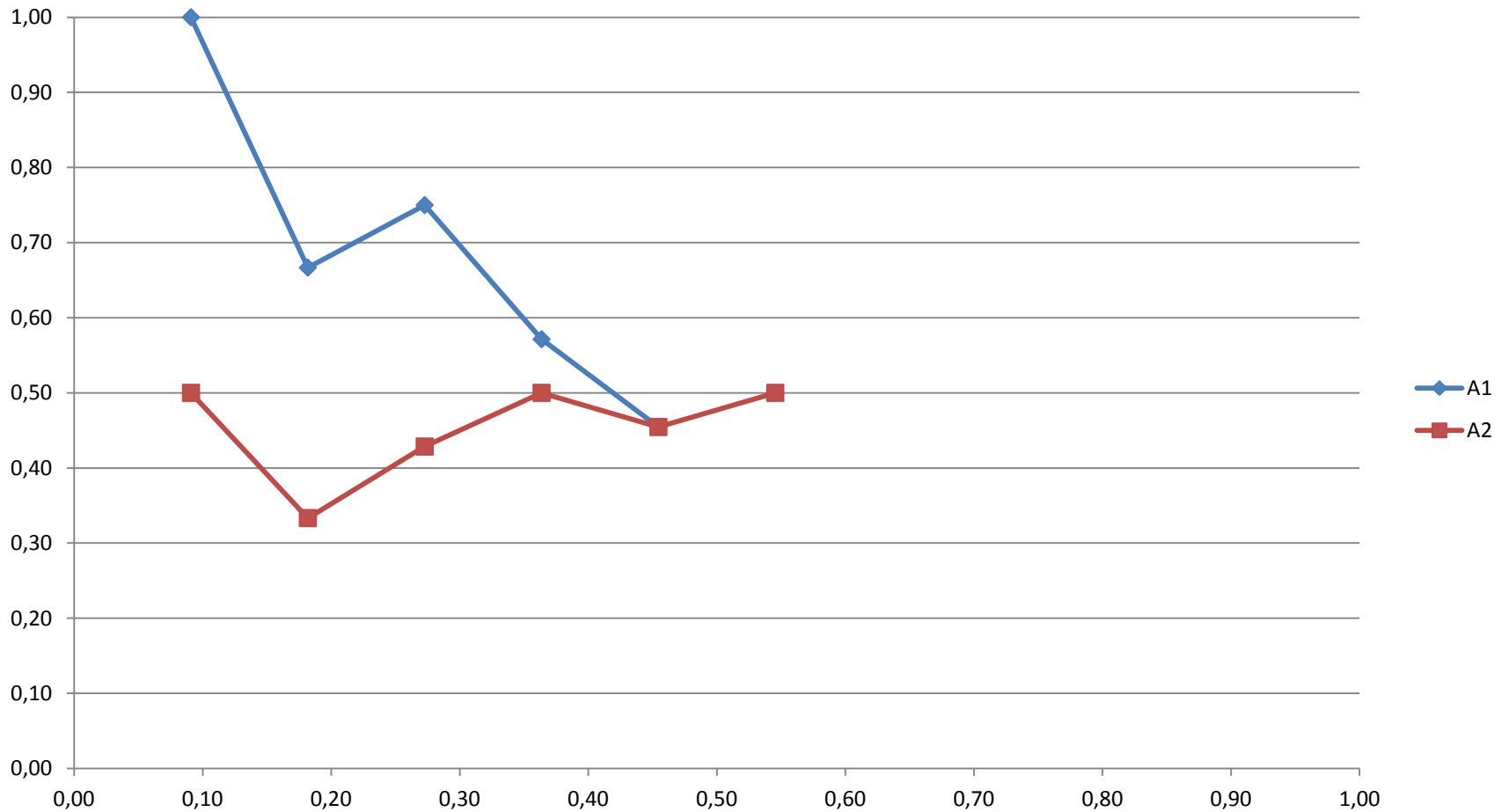
Results



- A1:
 - 0,455 Precision
 - 0,455 Recall
- A2:
 - 0,500 Precision
 - 0,545 Recall

RC-Lev	PR-A1	PR-A2
0,09	1,00	0,50
0,18	0,67	0,33
0,27	0,75	0,43
0,36	0,57	0,50
0,45	0,45	0,45
0,55		0,50
0,64		
0,73		
0,82		
0,91		
1,00		

Results Ex-04



Content Based Image Retrieval



- Motivation & Semantic Gap
- Perception
- Color Based Features
- Texture Based Features



Motivation



Lots of good reasons ...

- Visual information overload
 - Devices (cameras, mobile phones, etc.)
 - Communication (email, mo-blogs, etc.)
- Metadata not available
 - Time consuming
 - No automation

**Question: What is so special 'bout
Mona Lisa's smile?**



Semantic Gap



- Defined as
 - Inability of automatic understanding
 - Gap between high- and low-level features / metadata
- Actually hard task for humans also

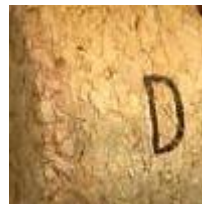


Image Similarity

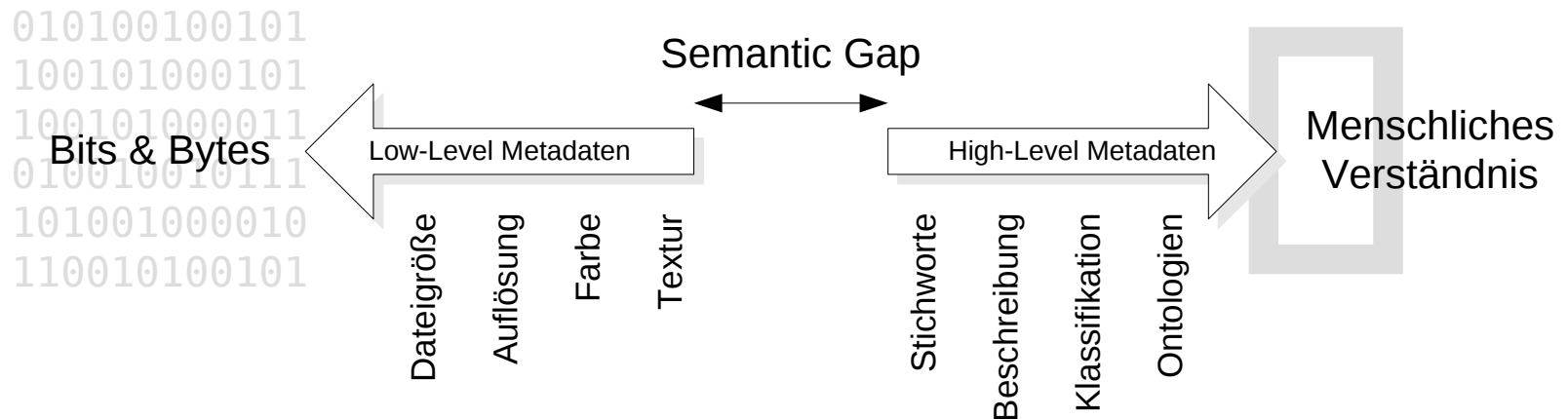


Are these two images similar?

Semantic Gap (1)



- General Definition: Santini & Jain (1998)



Applications



- Home User & Entertainment
 - Find picture of / from / at
 - Search & browse personal digital library
- Graphics & Design
 - Find picture representing something (Color in CD/CI, feeling, etc.)
- Medical Applications
 - Find images for diagnosis, documentation

Applications



- **Biology**
 - Finding similar animals, insects & plants
- **Weather forecasting**
 - Finding similar weather conditions
- **Advertisement**
 - Find similar products

Content Based Image Retrieval



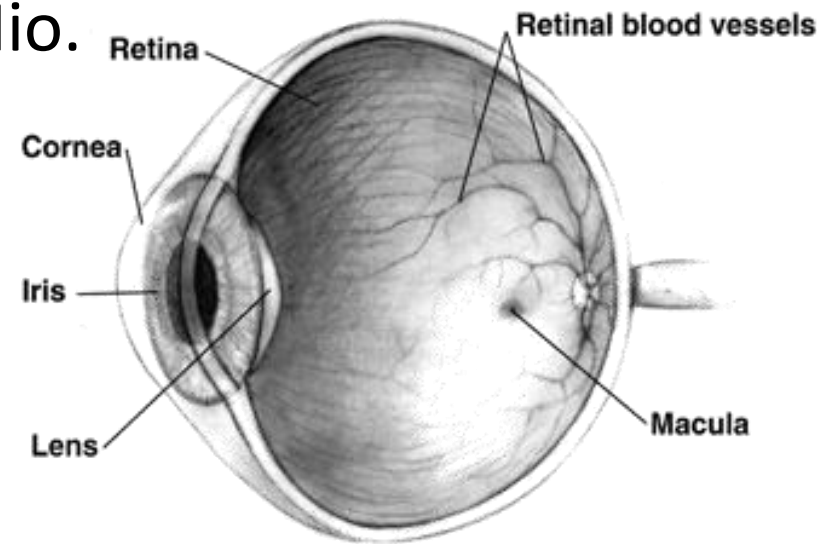
- Motivation & Semantic Gap
- Perception
- Color Based Features
- Texture Based Features



Perception



- The **eye** as instrument of perception
- Sensory capabilities
 - Cones (bright light): 6-7 Mio.
 - Rods (dim-light): 75-150 Mio.
 - Brain 'corrects' vision
 - e.g. blind spot

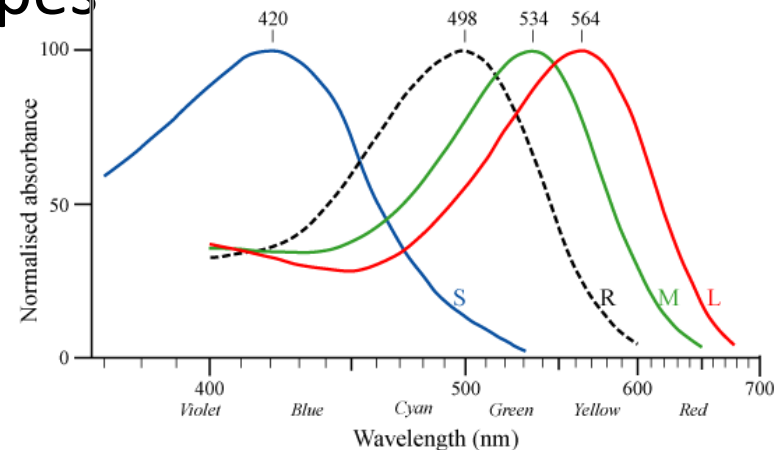


Color & Color Spaces



S-, M- and L-cones: Blue, green and red

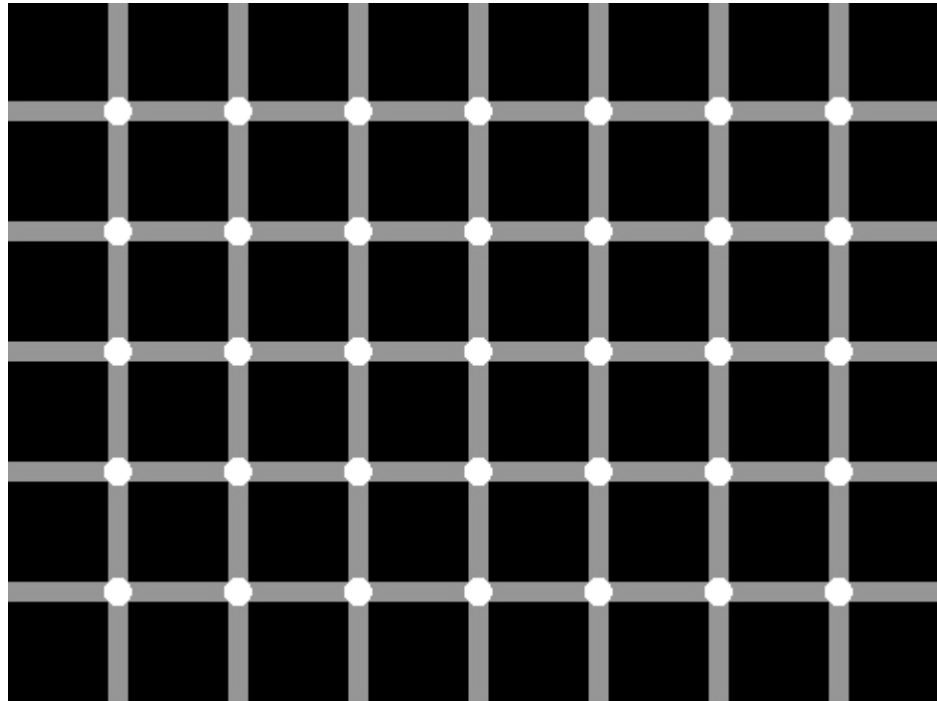
- RGB based on these three colors
- CIE models perception better
 - Responsiveness of cone types
 - Number of cones / types
 - etc.



The human eye ...



- Count the black dots on the image:



The human eye ...



- Rabbit or duck?



The human eye ...



- Anamorphic illusions



See e.g. <http://users.skynet.be/J.Beever/pave.htm>

Anamorphic Illusions (Julian Beever)



What are (digital) images?



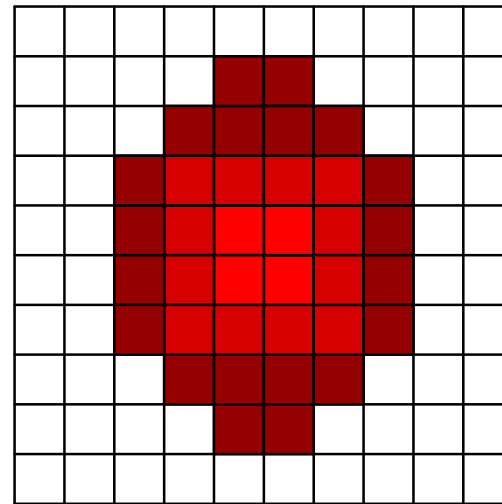
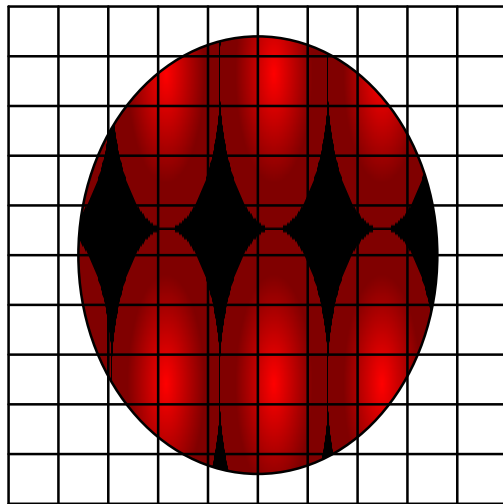
- An Image is
 - Created by a set of photons
 - With different frequency
 - Moving from different sources
 - Along different vectors
 - A representation of sensor unit activation
 - Activated by the set of photons
- Storing an image
 - Based on the set of photons ???



Sampling & Quantization



- Capturing continuous images on sensors
 - Sampling: Continuous to matrix
 - Quantization: Continuous color to value



Sampling & Quantization



- Size of a captured image:
 - # of samples (width*height) * # of colors



Content Based Image Retrieval



- Motivation & Semantic Gap
- Perception
- Color Based Features
- Texture Based Features



Accessing Pixel Data in Java



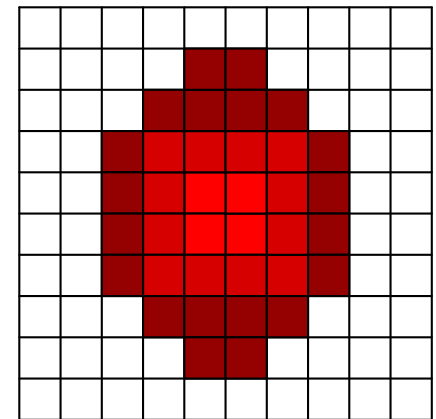
```
// opening an image file
BufferedImage image = ImageIO.read(new File("ferrari-01.jpg"));
// pixel data is in the raster
WritableRaster raster = image.getRaster();
// create an object for the pixel data:
int[] pixel = new int[3];
// access pixel data:
for (int x = 0; x < raster.getWidth(); x++) {
    for (int y = 0; y < raster.getHeight(); y++) {
        // access pixel data here ...
        raster.getPixel(x, y, pixel);
    }
}
```



Histogram



- Count the use of different colors
- Algorithm:
 - Allocate int array h with dim = # of colors
 - Visit next pixel -> it has color with index i
 - Increment h[i]
 - IF pixels left THEN goto line 2
- Example: 4 colors, 10*10 pixels
 - histogram: [4, 12, 20, 64]



Histogram



```
int[] histogram = new int[32];  
for (int x = 0; x < raster.getWidth(); x++) {  
    for (int y = 0; y < raster.getHeight(); y++) {  
        histogram[quantize(raster.getPixel(x, y, pixel))]++;  
    }  
}
```

Luminance Histogram



```
public static int quantize(int[] pixel) {  
    int tmp = pixel[0] + pixel[1] + pixel[2];  
    return (int) ((float) tmp / (3f*8f));  
}
```

- Quantizing grey values to 32 bins

Luminance Histogram



Color Histogram



```
public static int quantize(int[] pixel) {  
    int tmp = pixel[0]*pixel[1]*pixel[2];  
    return (int) ((float) tmp / Math.pow(2, 19));  
}
```

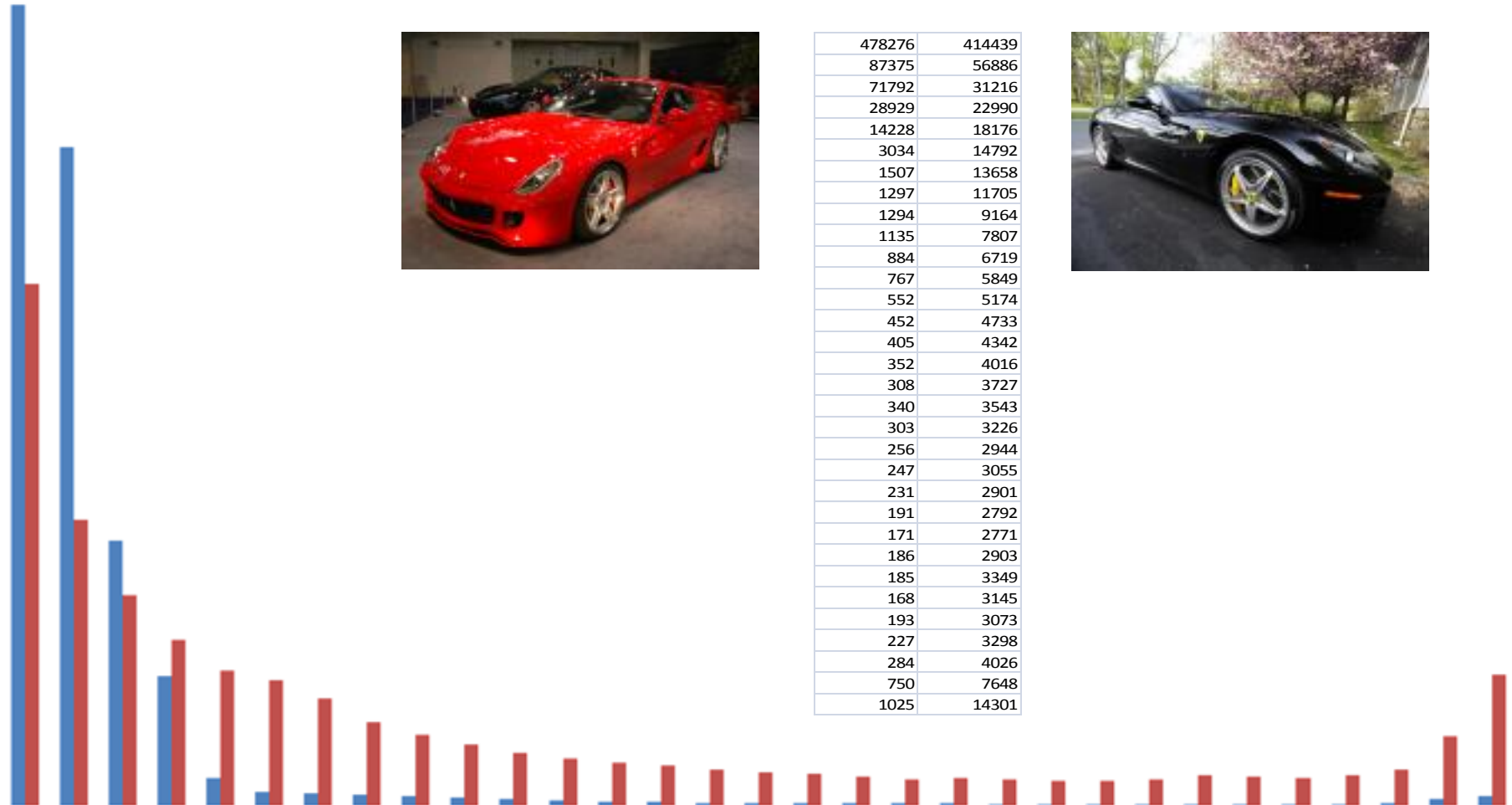
- Quantizing RGB color to 2^5 bins ...
 - Note that this should be based on a palette ...



Color Histogram



478276	414439
87375	56886
71792	31216
28929	22990
14228	18176
3034	14792
1507	13658
1297	11705
1294	9164
1135	7807
884	6719
767	5849
552	5174
452	4733
405	4342
352	4016
308	3727
340	3543
303	3226
256	2944
247	3055
231	2901
191	2792
171	2771
186	2903
185	3349
168	3145
193	3073
227	3298
284	4026
750	7648
1025	14301



Color Histogram



- Strategies:
 - Quantize if too many colors
 - Normalize histogram (different image sizes)
 - Weight colors according to use case
 - Use (part of) color space according to domain
- Distance / Similarity
 - Assumption: All images have the same colors
 - L_1 or L_2 is quite common

Histogram Similarity



- L1 (Manhattan, city block) distance

$$d_1(\mathbf{p}, \mathbf{q}) = \|\mathbf{p} - \mathbf{q}\|_1 = \sum_{i=1}^n |p_i - q_i|,$$

- L2 (Euclidean) distance

$$d(\mathbf{p}, \mathbf{q}) = d(\mathbf{q}, \mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2} = \sqrt{\sum_{i=1}^n (q_i - p_i)^2}.$$

- Jensen-Shannon Divergence

$$d_{JSD}(H, H') = \sum_{m=1}^M H_m \log \frac{2H_m}{H_m + H'_m} + H'_m \log \frac{2H'_m}{H'_m + H_m}$$

Histogram Similarity



```
// --- L1 ---
distance = 0;
for (int i = 0; i < hist2.length; i++) {
    distance += Math.abs(hist2[i] - hist1[i]);
}
System.out.println("L1 " + distance);

// --- L2 ---
distance = 0;
for (int i = 0; i < hist2.length; i++) {
    distance += (hist2[i] - hist1[i]) * (hist2[i] - hist1[i]);
}
distance = (float) Math.sqrt(distance);
System.out.println("L2 " + distance);

// --- JSD ---
distance = 0;
for (int i = 0; i < hist2.length; i++) {
    distance += (float) hist1[i] * Math.log(2f * (float) hist1[i] / ((float) hist1[i] + (float) hist2[i])) +
                (float) hist2[i] * Math.log(2f * (float) hist2[i] / ((float) hist1[i] + (float) hist2[i]));
}
distance = (float) Math.sqrt(distance);
System.out.println("JSD " + distance);
```

Histogram Similarity



- Luminance

- L1 436406.0
- L2 77265.8
- JSD 343.3



- RGB Color

- L1 82706.0
- L2 58174.6
- JSD 281.5

Color Histogram



- **Benefits**
 - Easy to compute, not depending on pixel order
 - Matches human perception quite well
 - Quantization allows to scale size of histogram
 - Invariant to (lossless) rotation & reflection
- **Disadvantages**
 - Distribution of colors not taken into account
 - Image scaling changes color

Dominant Color



- Reduce histogram to dominant colors
 - e.g. for 64 colors c0-c63:
 - image 1: c12 -> 23%, c33 -> 6%, c2 -> 2%
 - image 2: c11 -> 43%, c2 -> 12%, c54 -> 10%
- Distance function in 2 aspects:
 - Difference in amount (percentage)
 - Difference between colors (c11 vs. c12)
- Further aspects:
 - Diversity and distribution

Dominant Color



- **Benefits:**
 - Small feature vectors
 - Easily understandable & intuitive
 - Similarity of color pairs (light vs. dark red, etc.)
 - Invariant to rotation & reflection
- **Disadvantages**
 - Similarity of color pairs no trivial problem
 - Dominant colors might not represent semantics

Color Distribution



- Index dominant color in image segment
 - e.g. $8 \times 8 = 64$ image segments
 - feature vector has 64 dimensions
 - One for each segment
 - color index is the entry on segment dimension
 - e.g. 16 colors [2, 0, 3, 3, 8, 4, ...]



Color Distribution



```
BufferedImage image = ImageIO.read(new File("ferrari-01.jpg"));  
// created instance of scaled image:  
BufferedImage scaled = new  
    BufferedImage(8,8,BufferedImage.TYPE_INT_RGB);  
// scale image (hardware acceleration)  
scaled.getGraphics().drawImage(image,  
    0, 0, 8, 8, // destination  
    0, 0, image.getWidth(), image.getHeight(), // source  
    null);
```



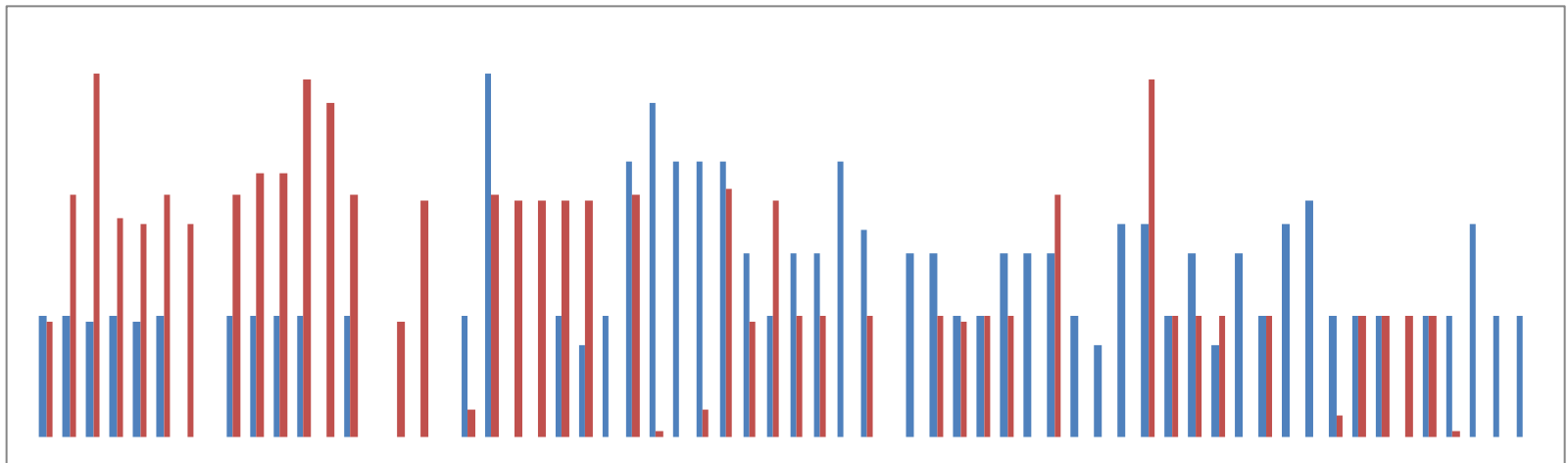
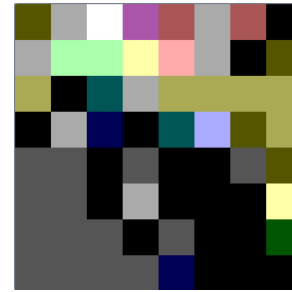
Color Distribution



```
// quantize and create histogram
WritableRaster raster = scaled.getRaster();
int[] hist = new int[64];
// temporary objects (speed)
int[] pixel = new int[3];
int tmp;
for (int x = 0; x < raster.getWidth(); x++) {
    for (int y = 0; y < raster.getHeight(); y++) {
        raster.getPixel(x,y,pixel);
        tmp = quantize(pixel);
        hist[y*8+x]=tmp;
        // set pixel in scale version for visualization:
        raster.setPixel(x,y,ColorHistogram.palette64[tmp]);
    }
}
```



Color Distribution



Color Distribution



- Similarity
 - L_1 or L_2 are commonly used
- Benefits
 - Works fine for many scenarios
 - clouds in the sky, portrait photos, etc.
 - Mostly invariant to scaling
- Disadvantages
 - Colors might not represent semantics
 - Find quantization fitting to domain / perception
 - Rotation & reflection are a problem

Color Correlogram



- Histogram on
 - how often **specific colors** occur
 - in the **neighbourhood** of each other
- Histogram size is $(\# \text{ of colors})^2$
 - For each color an array of neighboring colors

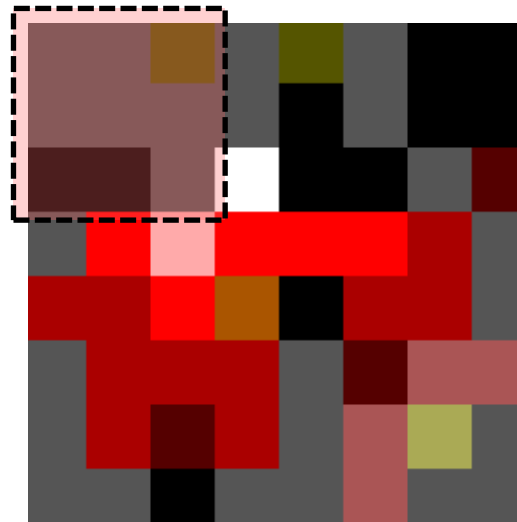
Color Correlogram



	red	green	blue
red	12	3	14
green	3	16	8
blue	14	8	23

For red pixels we find 3 green pixels all over the image in a neighborhood p.

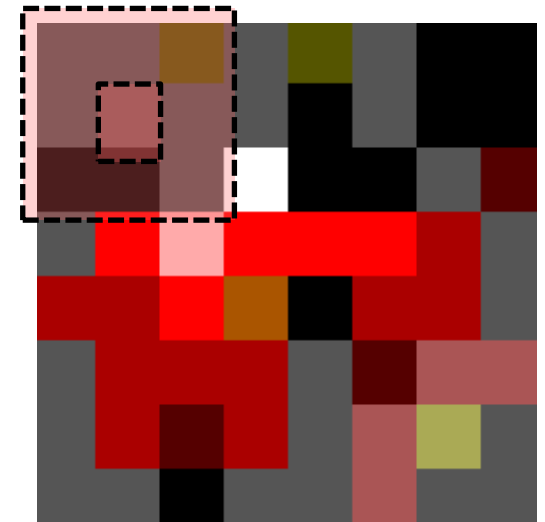
Color Correlogram



Color Correlogram



- For each window position
- Consider center color
- Add surrounding colors to histogram



Color Correlogram



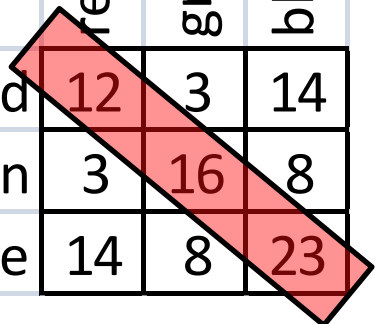
- Extraction algorithm
 - Allocate array $h[\text{\#colors}][\text{\#colors}]$ all zero
 - Visit next pixel p
 - For each pixel q in neighborhood of p :
 - increment $h[\text{color}(p)][\text{color}(q)]$
 - IF pixels left THEN goto line 2
- Algorithm is rather slow
 - Depends on size of neighborhood
 - Typically determined by city block (L1) distance

Color Correlogram



- Auto Color Correlogram
 - Just indexing how often $color(p)$ occurs in neighborhood of pixel p
 - Simplifies the histogram to size # of colors
 - Measure e.g. how red comes with red etc.

	red	green	blue
red	12	3	14
green	3	16	8
blue	14	8	23



Color Correlogram



- **Similarity**
 - L_1 or L_2 are commonly used
- **Benefits**
 - Integrates color as well as distribution
 - Works fine for many scenarios
 - Mostly invariant to rotation & reflection
- **Disadvantages**
 - Find appropriate neighborhood size
 - Find quantization fitting to domain / perception
 - Rather slow indexing / extraction

Color Correlogram

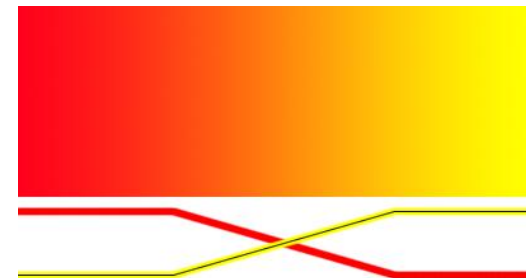


- Integrating different pixel features to correlate
 - **Gradient Magnitude** (intensity of change in the direction of maximum change)
 - **Rank** (intensity variation within a neighborhood of a pixel)
 - **Texturedness** (number of pixels exceeding a certain level in a neighborhood)

Fuzzy Color Histogram



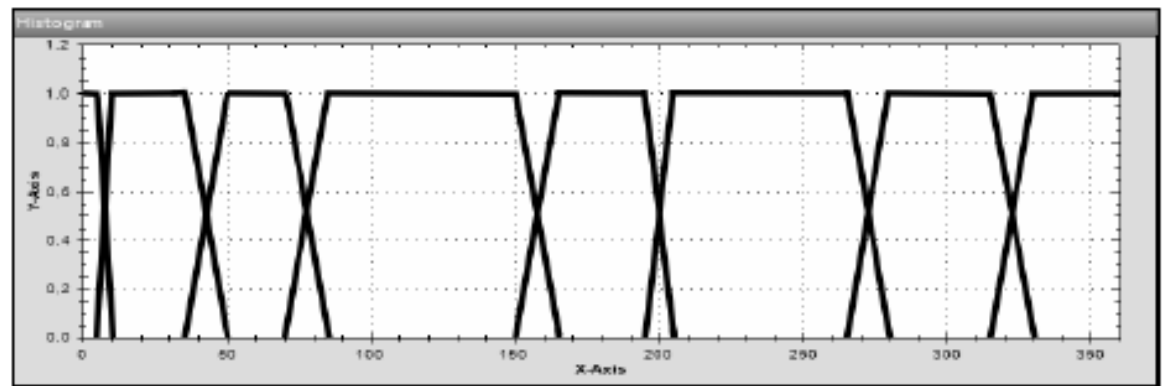
- Binary decision not necessary
- Pixel can be half red, half yellow
- Fuzziness:
 - membership functions $m_i(r,g,b)$
 - For each bin i : $m_i(r,g,b)$ in $[0,1]$
 - Sum of all $m_i = 1$.



Fuzzy Color Histogram (FCTH)



- Fuzzy membership function for HSV in FCTH
 - (0) Red to Orange
 - (1) Orange
 - (2) Yellow
 - (3) Green
 - (4) Cyan
 - (5) Blue
 - (6) Magenta
 - (7) Blue to Red

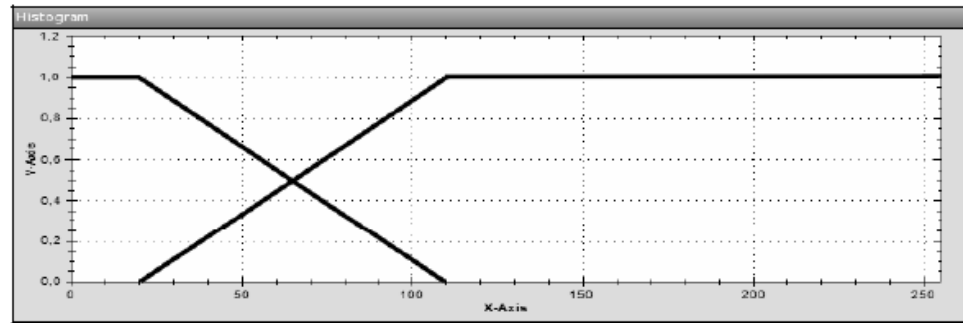


*S. A. Chatzichristofis and Y. S. Boutalis, "FCTH: FUZZY COLOR AND TEXTURE HISTOGRAM
A LOW LEVEL FEATURE FOR ACCURATE IMAGE RETRIEVAL", WIAMIS IEEE 2008*

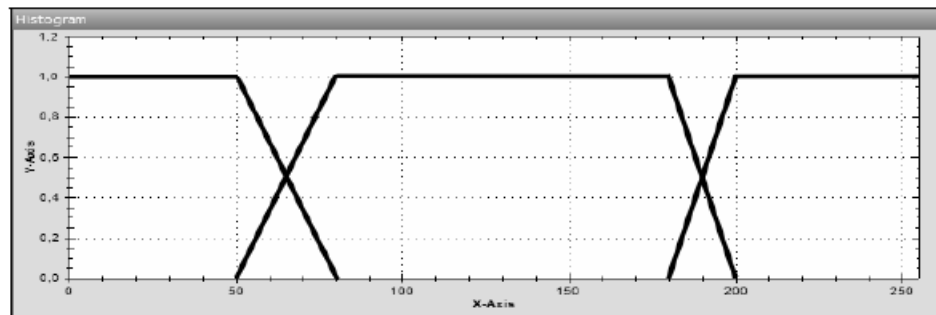
Fuzzy Color Histogram (FCTH)



- Saturation: white vs. color



- Value: black vs. grey vs. color



Content Based Image Retrieval



- Motivation & Semantic Gap
- Perception
- Color Based Features
- **Texture & Shape Features**



Texture & Shape Features



- Indexing non color features in image
 - Outlines, edges of regions
 - Overall characteristics like coarseness and regularity



Spatial Filtering



- Methods for *enhancing* the image
- Normally a kernel or filter is used:
 - A matrix which is applied to the image
 - In a linear transformation

Spatial Filtering



194	128	102	197	69
162	68	103	144	115
121	85	57	27	14
24	183	192	239	150
92	93	154	138	170

194	128	102	197	69
162	68	103	144	115
121	85	122	27	14
24	183	192	239	150
92	93	154	138	170

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Spatial Filtering



- This is a simple smoothing kernel
- Other operations
 - Sharpen
 - Gradient
 - ...



Edge Detection



- Spatial Filtering with Sobel Kernel

```
// read image
BufferedImage image = ImageIO.read(new File("ferrari-01.jpg"));
// converting to grey
image = convertImageToGrey(image);
// spatial filtering
BufferedImage filteredImage =
    new BufferedImage(image.getWidth(), image.getHeight(), image.getType());
// create Sobel kernel
Kernel kernel = new Kernel(3, 3, new float[] {1,2,1,0,0,0,-1,-2,-1});
ConvolveOp op = new ConvolveOp(kernel);
// filter image
op.filter(image, filteredImage);
```

Convert to grey in Java



```
WritableRaster inRaster = image.getRaster();
BufferedImage result = new BufferedImage(image.getWidth(), image.getHeight(),
    BufferedImage.TYPE_BYTE_GRAY);
WritableRaster outRaster = result.getRaster();
int[] p = new int[3];
float v = 0;
for (int x = 0; x < inRaster.getWidth(); x++) {
    for (int y = 0; y < inRaster.getHeight(); y++) {
        inRaster.getPixel(x, y, p);
        v = Math.round((p[0] + p[1] + p[2])/3f);
        for (int i = 0; i < p.length; i++) {
            p[i] = (int) v;
        }
        outRaster.setPixel(x,y, p);
    }
}
```

Edge Detection



Edge Detection



- Apply two Kernels
 - with results L_x and L_y
- Then compute the gradient magnitude

$$|\nabla L| = \sqrt{L_x^2 + L_y^2}$$

- Edge direction: $\arctan(L_y/L_x)$

1	2	1
0	0	0
-1	-2	-1
1	0	-1
2	0	-2
1	0	-1

Edge Detection



Tamura Features

Tamura & Mori (1978)



- Widely used in CBIR
 - E.g. IBM QBIC
- 6 texture features
 - Coarseness, contrast, directionality
 - Line-likeness, regularity, and roughness
- Good overview is provided in:
 - Thomas Deselaers, “Features for Image Retrieval”, Thesis, RWTH Aachen, Dec. 2003

Tamura Features

Tamura & Mori (1978)



- Coarseness
 - Pixel diversity in neighborhoods
- Contrast
 - Using mean and variance of an image
- Directionality
 - Horizontal and vertical derivatives (like Sobel)

Directionality Histogram



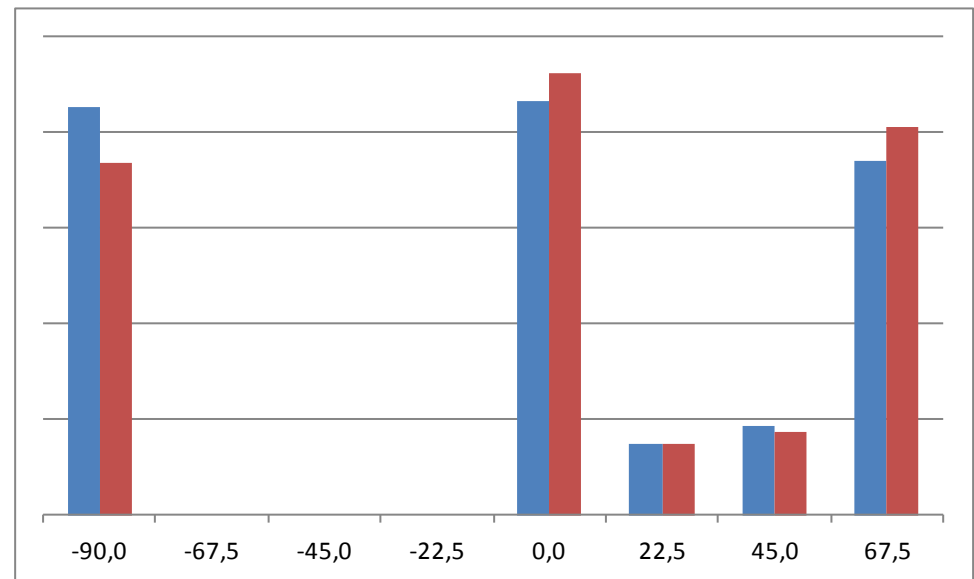
```
// 8-bin directionality histogram ..
int hist[] = new int[8];
for (int i = 0; i < hist.length; i++)
    hist[i] = 0;

for (int x = 0; x < rasterX.getWidth(); x++) {
    for (int y = 0; y < rasterX.getHeight(); y++) {
        rasterX.getPixel(x,y,pixelX);
        rasterY.getPixel(x,y,pixelY);
        // compute directionality histogram:
        double tmpAngle = Math.PI/2 + Math.atan((double) pixelY[0] / (double) pixelX[0]);
        tmpAngle = Math.floor(8d * tmpAngle / Math.PI);
        tmpAngle = Math.min(7d, tmpAngle);
        hist[((int) tmpAngle)]++;
    }
}
```

Directionality Histogram



- Angle histogram with 8 bins
- $[-90, -67.5)$, $[-67.5, -45)$, ...



Joint Histograms



- Color & texture properties per pixel
 - E.g. color (8 bins) + gradient (4 bins)
- E.g. directionality histogram per color bin
 - I.e. 4 times a color histogram

Joint Histogram



	0°-45°	45°-90°	90°-135°	135°-180°	Σ
red	88	51	93	10	241
orange	29	29	53	34	144
yellow	57	58	22	88	224
green	6	13	58	8	85
blue	25	86	43	47	200
Σ	204	236	268	186	

88 red pixels with a gradient direction of 0-45°

Color Histogram

Directionality Histogram

Joint Histograms



- **Strategies**
 - Find good texture properties
 - Minimize overall number of bins
- **Benefits**
 - Works better than pure color histograms
- **Disadvantages**
 - Typically slower extraction
 - Higher number of bins

Linear Search



- Corpus contains K images,
- Represented by feature vectors
 - f_k with k in $[0, K-1]$
- We have a distance funktion
 - $d(f_i, f_j) \rightarrow [0, \infty]$

Linear Search



- Given a query q
 - also being a feature vector
- Find a
 - ranked list of
 - the $n < K$ most relevant images
 - having minimum distance to the query

Linear Search - Approach



- Create an “index”
 - a list of feature vectors -> image file
- With a query
 - traverse list
 - (re-) order result set with fixed length

Linear Search - Complexity



- Given
 - an index of K image feature vectors
 - searching for N relevant images
- Complexity is based on
 - Taking a look at each of the K images
 - modifying a sorted list of N relevant images
- If N is “small” then
 - complexity is $O(K)$

Linear Search:

How it is done in Lire



- Lire uses Lucene for storage on HDD
 - Lucene Document object
 - Lucene Field for image file path and features
- DocumentBuilder class
 - creates Document from BufferedImage
 - returns Document
 - encapsulates feature extraction
 - stores file path in text field
 - stores feature in byte[] payload

Linear Search: How it is done in Lire



- ImageSearcher
 - encapsulates feature
 - opens each Lucene Document
 - parses byte[] payload (done in LireFeature)
 - compares feature to query
 - manages result list
 - returns results

Linear Search: How it is done in Lire



- ImageSearcher code (Lire):

```
int docs = reader.numDocs();
for (int i = 0; i < docs; i++) {
    // bugfix by Roman Kern
    if (hasDeletions && reader.isDeleted(i)) {
        continue;
    }

    Document d = reader.document(i);
    float distance = getDistance(d, lireFeature);
    assert (distance >= 0);
    // ... adapting result list
}
```

Linear Search: How it is done in Lire



- Lucene
 - provides really fast file I/O
 - index management & additional text search
- Lire
 - generic use of different feature vectors
 - encapsulates (some) Lucene functions
- Runtime
 - 121,379 images indexed with CEDD
 - took 0.33 seconds search time

Exercise 04



- Program a joint histogram feature
 - fuzzy color histogram
 - some texture feature
 - e.g. edge direction, intensity, contrast
 - see “Features for Image Retrieval”,
<http://goo.gl/rwZAM>
- Do a linear search on the Ferrari data set

Thank you ...



... for your attention