



Content Based Image Retrieval

Natalia Vassilieva nvassilieva@hp.com HP Labs Russia



© 2008 Hewlett-Packard Company

Tutorial outline

- Lecture 1
 - Introduction
 - Applications
- Lecture 2
 - Performance measurement
 - Visual perception
 - Color features
- Lecture 3
 - Texture features
 - Shape features
 - Fusion methods
- Lecture 4
 - Segmentation
 - Key points detection
- Lecture 5
 - Multidimensional indexing
 - Survey of existing systems



Lecture 2 Performance measurement Visual perception Color features



Lecture 2: Outline

- Performance measurement
 - Retrieval effectiveness
- Some facts about human visual perception
- Color features
 - Color fundamentals
 - Color spaces
 - Color features: histograms and moments
 - Comparison



Performance measurement

- Performance concerns
- Efficiency
 - Important due to the large data size
- Retrieval effectiveness
 - No similarity metric which exactly conforms to human perception

Problems in effectiveness evaluation

- Define a common image collection
 - Corel Photo CDs
 - Brodatz texture collection: <u>http://www.ux.uis.no/~tranden/brodatz.html</u>
 - CoPhIR: http://cophir.isti.cnr.it/whatis.html
 - Participate in ImageCLEF, TRECVID, imageEVAL, ROMIP
- Obtain relevance judgement
 - Use of collections with predefined subsets (Corel collection)
 - Image grouping (medical)
 - Simulating users
 - User judgements
 - Pooling
 - Different types of judgement data (relevant not relevant, ranking, ...)



Effectiveness measurement

• "You can see, that our results are better"

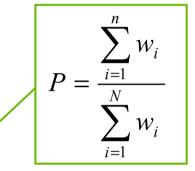




Effectiveness measurement

- "You can see, that our results are better"
- User comparison
- Numerical-valued measures
 - Rank of the best image
 - Average rank of relevant images
 - Percentage of weighted hits-
 - Percentage of similarity ranking

$$S(i) = \sum_{k=K_1}^{K_2} Q(i,k), \quad K_1 = P(i) - \sigma(i), \quad K_2 = P(i) + \sigma(i)$$



LABShp

Effectiveness measurement (2)

Numerical-valued measures

- Recall and precision

 $precision = \frac{\text{No. relevant documents retrieved}}{\text{Total No. documents retrieved}},$

 $recall = \frac{\text{No. relevant documents retrieved}}{\text{Total No. relevant documents in the collection}}$

- Average recall/precision
- Recall at N, Precision at N
- F-measure



Effectiveness measurement (3)

Numerical-valued measures

- Target testing
- Error rate

 $Error rate = \frac{No. non-relevant images retrieved}{Total No. images retrieved}$

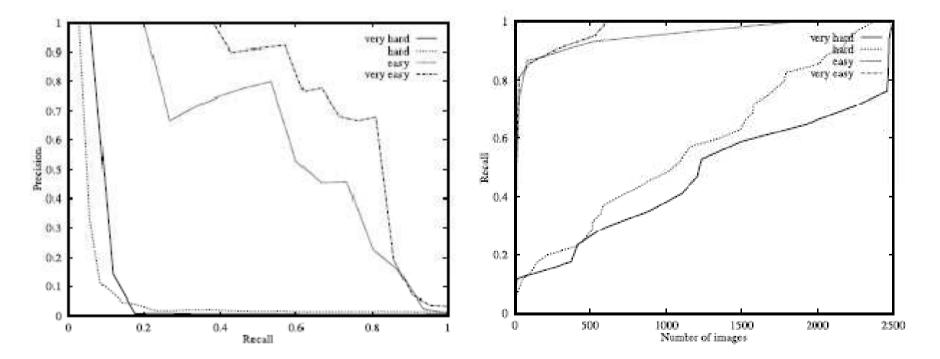
- Retrieval efficiency

 $\mathbf{R} \text{etrieval efficiency} = \begin{cases} \frac{\text{No. relevant images retrieved}}{\text{Total No. images retrieved}} \\ \text{if No. retrieved} > \text{No. relevant,} \\ \frac{\text{No. relevant images retrieved}}{\text{Total No. relevant images}} & \text{otherwise.} \end{cases}$



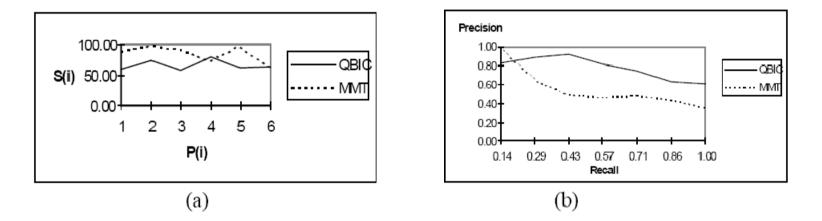
Effectiveness measurement (3)

- Graphical representations
 - Precision versus Recall graphs
 - Precision at N versus N, Recall at N versus N
 - Retrieval accuracy versus noise graph



Effectiveness measurement (4)

Different measurement (QBIC versus MMT)



Average performance measured using (a) the percentage of similarity ranking method (b) recall and precision pair



Lecture 2: Outline

Performance measurement
– Retrieval effectiveness

Some facts about human visual perception

- Color features
 - Color fundamentals
 - Color spaces
 - Color features: histograms and moments
 - Comparison



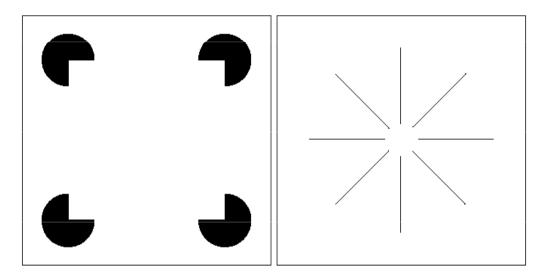
- We are driven by a desire to make meanings (We all seem to 'see things' in inkblots, flames, stains, clouds and so on.)
- Human visual perception is self-learning
 - If you are an European, it is hard to recognize Japanese and Chinese faces
 - We are looking for the known objects in the picture







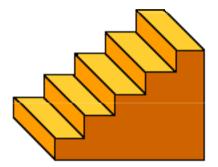
- We are looking for the known objects in the picture



Some well known optical illusions

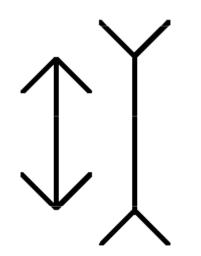


 Cultural and environmental factors affects the way we see things



Are these stairs goes up or down?

 Arabs would read this (right to left) as a set of stairs going down



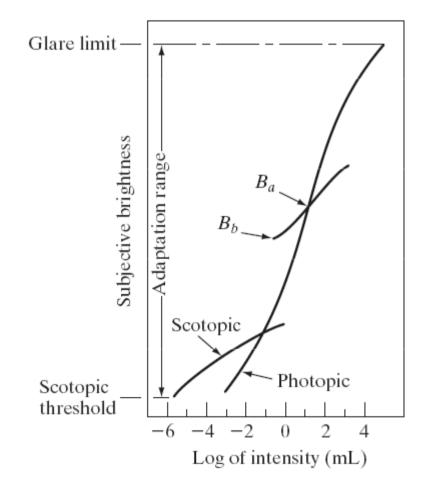
Is left line shorter than the right •One?outside corner of a building

• Right: inside corner of a room

Inside corner may appear to be nearer (and therefore larger)



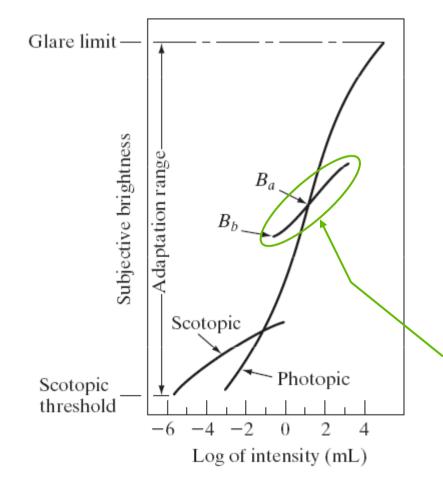
Brightness adaptation and discrimination



- Range of light intensity levels to which human visual system can adapt: order of 10¹⁰
- Subjective brightness (perceived intensity) is a logarithmic function of the actual light intensity

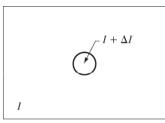


Brightness adaptation and discrimination

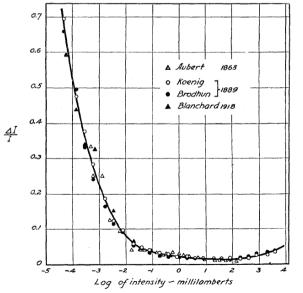


- The human visual system cannot operate over such a range (10¹⁰) simultaneously
- It accomplishes this variation by changing its overall sensitivity – brightness adaptation phenomena
- The range of subjective brightness that the eye can perceive when adapted to the level B_a
- B_a brightness adaptation level
- B_b below it all stimuli are perceived as black

Brightness adaptation and discrimination



Basic experimental setup used to characterize brightness discrimination.



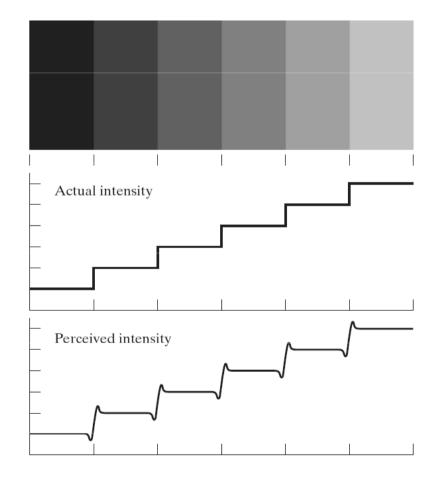
 The eye discriminates between changes in brightness at any specific adaptation level.

 $\frac{M_c}{I}$ – Weber ratio,

- ΔI_c the increment of illumination discriminable 50% of the time; I – background illumination.
- Small values of Weber ratio mean good brightness discrimination (and vice versa).
- At low levels of illumination brightness discrimination is poor (rods) and it improves significantly as background illumination increases (cones).



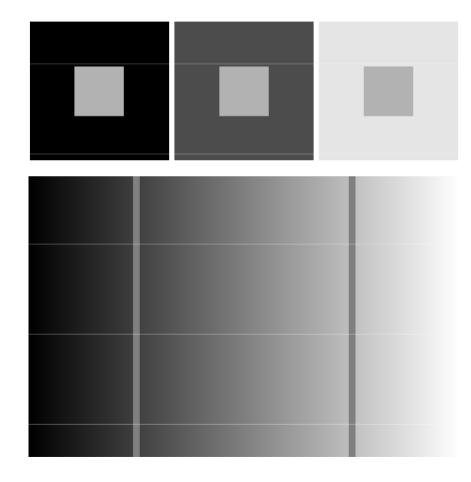
• Perceived brightness is not a simple function of intensity



 Mach band effect (Scalloped effect)



• Perceived brightness is not a simple function of intensity



Simultaneous contrast

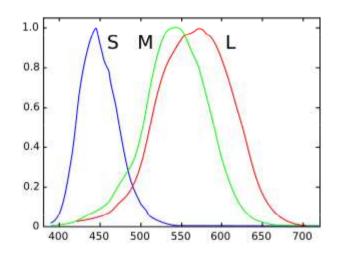


Lecture 2: Outline

- Performance measurement
 Retrieval effectiveness
- Some facts about human visual perception
- Color features
 - Color fundamentals
 - Color spaces
 - Color features: histograms and moments
 - Comparison



Color in the eye



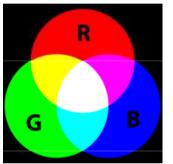
Normalized typical human cone cell responses (S, M, and L types) to monochromatic spectral stimuli

- Varying sensitivity of different cells in the retina (cones) to light of different wavelengths:
 - S-cones: short-wavelength (blue);
 - M-cones: middle-wavelength (green);
 - L-cones: long-wavelength (red).

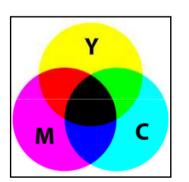
Cone type	Name	Range	Peak wavelength
S	β	400–500 nm	420–440 nm
М	γ	450–630 nm	534–545 nm
L	ρ	500–700 nm	564–580 nm



Primary and secondary colors



Mixture of lights (Additive primaries)



Mixture of pigments (Subtractive primaries)

- Due to different absorption curves of the cones, colors are seen as variable combinations of the so-called primary colors: red, green and blue.
- The primary colors can be added to produce the secondary colors of light: magenta (R+B), cyan (G + B), and yellow (R + G).
- For pigments and colorants, a primary color is the one that subtracts (absorbs) a primary color of light and reflects the other two.



- Brightness, hue, and saturation
 - Brightness is a synonym of intensity
 - Hue represents the impression related to the dominant wavelength of the color stimulus
 - Saturation expresses the relative color purity (amount of white light in the color)
 - Hue and Saturation taken together are called the chromaticity coordinates (polar system)



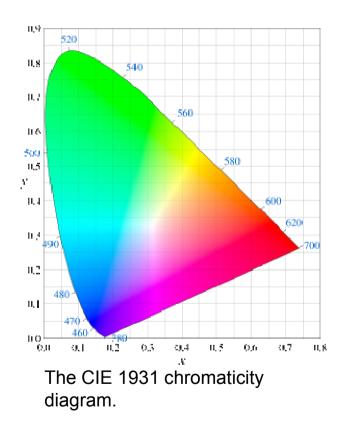
- From tristimulus values to chromaticity coordinates
 - The amounts of red, green, and blue needed to form any particular color are called the tristimulus values and denoted by X, Y, and Z
 - The chromaticity coordinates x and y (Cartesian system) are obtained as:

$$x = \frac{X}{X+Y+Z}, \quad y = \frac{Y}{X+Y+Z}, \quad z = \frac{Z}{X+Y+Z}$$

x + y + z = 1



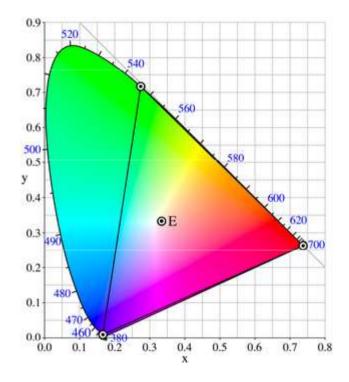
Color fundamentalsCIE xy Chromaticity Diagram



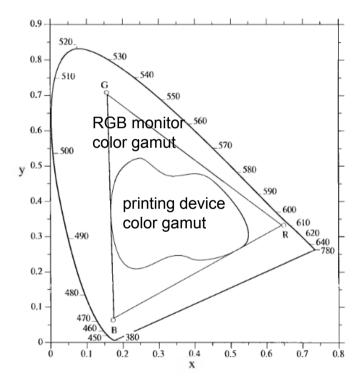
- Created by the International Commission on Illumination (CIE) in 1931.
- Function of x (red) and y (green): z = 1 - (x + y).
- The outer boundary is the spectral (monochromatic) locus, wavelengths shown in nm.
- (x,y) = (1/3,1/3) is a flat energy spectrum point (point of equal energy).
- Any point on the boundary is completely saturated.
- Boundary \rightarrow point of equal energy : saturation $\rightarrow 0$



Color Gamut



Gamut of the CIE RGB primaries and location of primaries on the CIE 1931 xy chromaticity diagram.



Typical gamuts of a monitor and of a printing device.



Lecture 2: Outline

- Performance measurement
 - Retrieval effectiveness
- Some facts about human visual perception

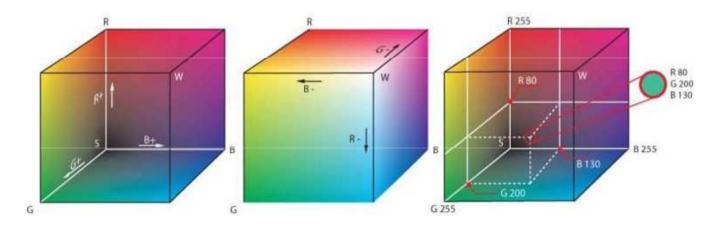
Color features

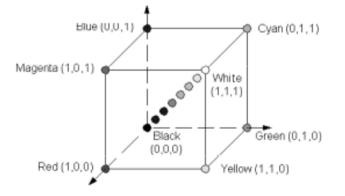
- Color fundamentals
- Color spaces
- Color features: histograms and moments
- Comparison



- The purpose of a color space (or color model or color system) is to facilitate the specification of colors in some standard way.
- A color model provides a *coordinate system* and a *subspace* in it where each color is represented by a single point.
- Common color spaces:
 - RGB (monitors, video cameras),
 - CMY/CMYK (printers),
 - HSI/HSV/HSL/HSB (image processing),
 - CIE Lab (image processing).

RGB color space

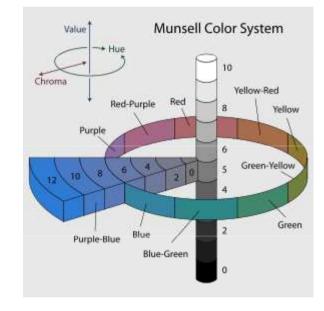




If R,G, and B are represented with 8 bits (24bit RGB image), the total number of colors is $(2^8)^3=16,777,216$



Munsell color system



- By Professor Albert H. Munsell in the beginning of the 20th century.
- Specifies colors based on 3 color dimensions, hue, value (lightness), and chroma (color purity or colorfulness).



Munsell hues; value 6 / chroma 6

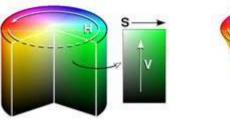


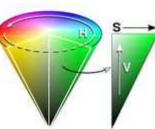
HSI/HSL/HSV/HSB color spaces

- RGB, CMY/CMYK are hardware oriented color spaces (suited for image acquisition and display).
- The HSI/... (Hue, Saturation, Intensity/Lightness/ Value/Brightness) are perceptive color spaces (suited for image description and interpretation).
- Allow the decoupling of chromatic signals (H+S) from the intensity signal (I).



HSI/HSL/HSV/HSB color spaces





Graphical depiction of HSV (cylinder and cone)

$$I = \frac{R + G + B}{3}$$
$$L = \frac{\max(R, G, B) + \min(R, G, B)}{2}$$

 $V = \max(R, G, B)$



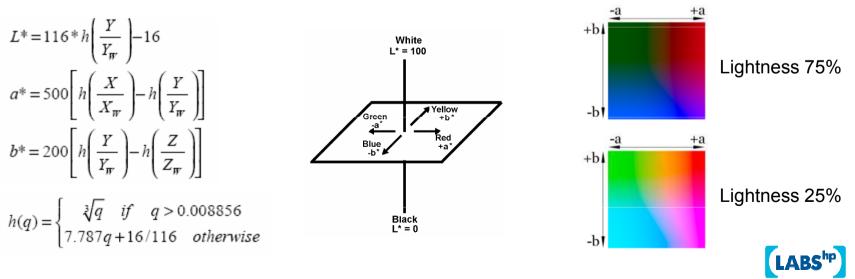
http://www.easyrgb.com/index.php?X=MATH

Graphical depiction of HSL

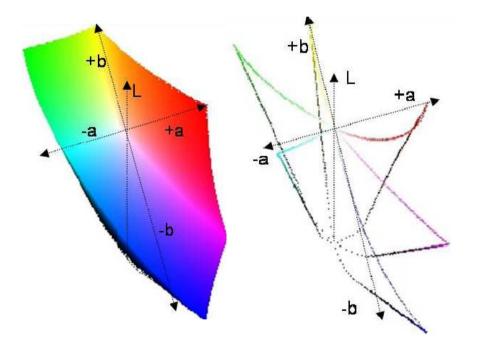


CIE L*a*b color space

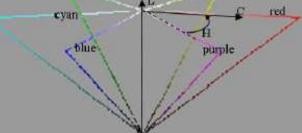
- It's a *device independent* and *perceptually uniform* color model.
- It allows the color gamuts of monitors and output devices to be related to one another.
- The L*a*b* components are given by



HCL color space



green yellow hlur puple green yellow cyan L c red



CIE Lab color space

HCL color space



Color spaces

HCL color space

$$\begin{split} L &= \frac{Q.Max(R,G,B) + (1-Q).Min(R,G,B)}{2} \\ C &= \frac{Q.(R-G|+|G-B|+|B-R|)}{3}, \text{ where } Q = e^{\alpha\gamma}, \alpha = \left(\frac{Min(R,G,B)}{Max(R,G,B)} \cdot \frac{1}{Y_0}\right), Y_0 = 100 \\ H &= \arctan\left(\frac{G-B}{R-G}\right) \end{split}$$

And finally to allow hue to vary in an interval from -180° to +180°:

 $\begin{array}{l} \text{if } ((R-G) \geq 0 \text{ and } (G-B) \geq 0), \text{ then } H = \frac{2}{3}H \\ \text{if } ((R-G) \geq 0 \text{ and } (G-B) < 0), \text{ then } H - \frac{4}{3}H \\ \text{if } ((R-G) < 0 \text{ and } (G-B) \geq 0), \text{ then } H = 180 + \frac{4}{3}H \\ \text{if } ((R-G) < 0 \text{ and } (G-B) < 0), \text{ then } H = \frac{3}{4}H - 180. \end{array}$



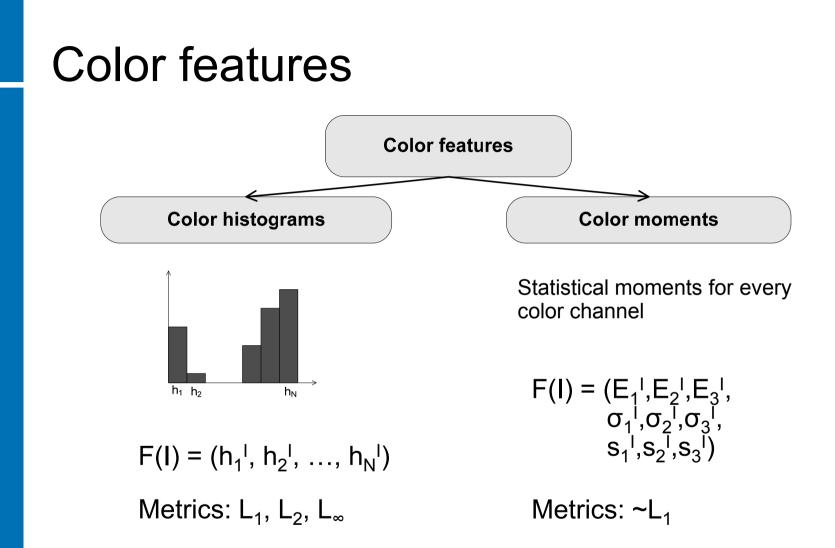
Lecture 2: Outline

- Performance measurement
 - Retrieval effectiveness
- Some facts about human visual perception

Color features

- Color fundamentals
- Color spaces
- Color features: histograms and moments
- Comparison



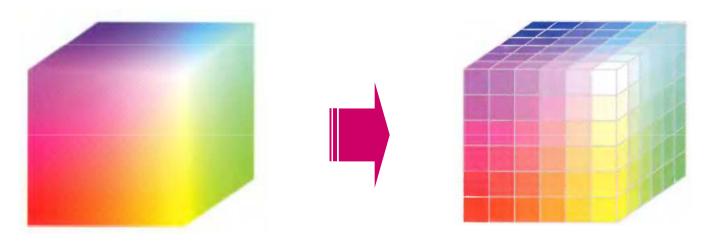


Stricker M., Orengo M. Similarity of Color Images. Proceedings of the SPIE Conference, vol. 2420, p. 381-392, 1995



Color histograms

Quantization of color space

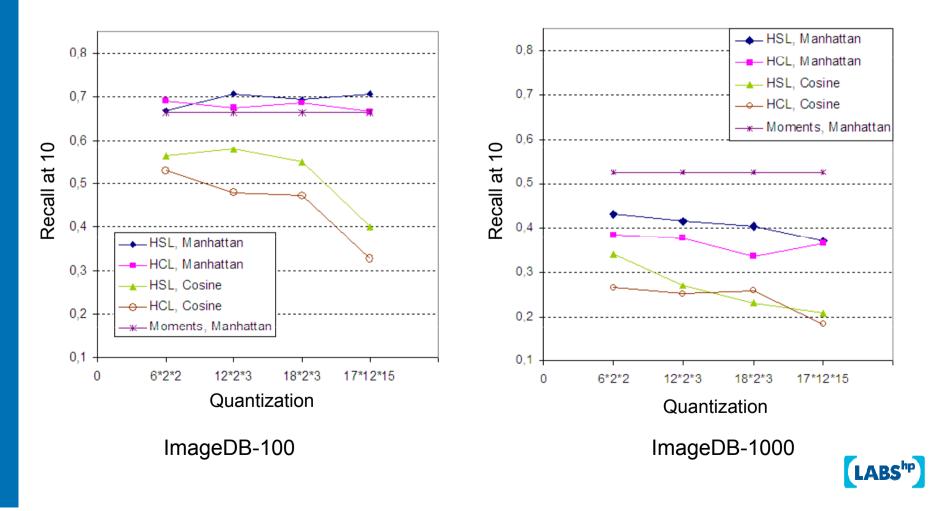


- Quantization is important: size of the feature vector.
- When no color similarity function used:
 - Too many bins similar colors are treated as dissimilar.
 - Too little bins dissimilar colors are treated as similar.



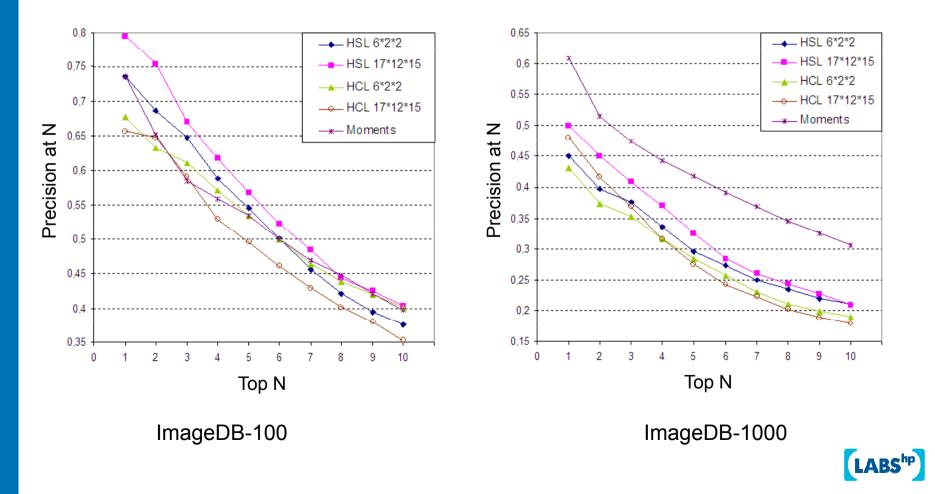
Color histograms

Quantization of color space: recall

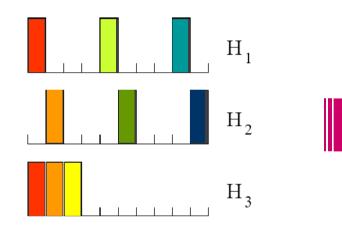


Color histograms

Quantization of color space: precision

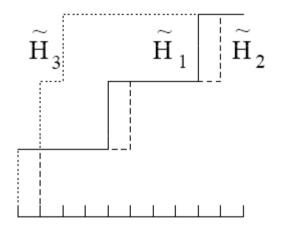


1. Colors similarity across histo bins is not considered:



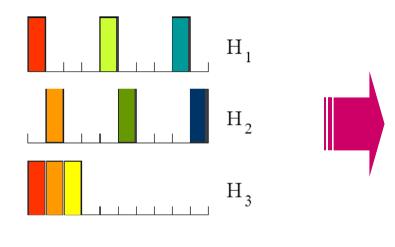
 $d(H_1, H_2) > d(H_1, H_3)$

Cumulative histograms





1. Colors similarity across histo bins is not considered:



 $d(H_1, H_2) > d(H_1, H_3)$

Cumulative histograms

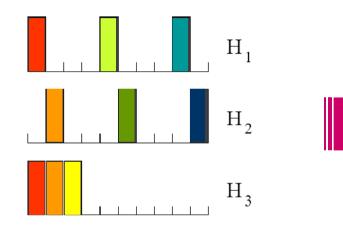
•
$$d(H_1, H_2) = \sqrt{(H_1 - H_2) \cdot A \cdot (H_1 - H_2)^T}$$

A – matrix with color similarity coefficients

Niblack W., Barber R., et al. The QBIC project: Querying images by content using color, texture and shape. In IS&T/SPIE International Symposium on Electronic Imaging: Science & Technology, Conference 1908, Storage and Retrieval for Image and Video Databases, Feb. 1993

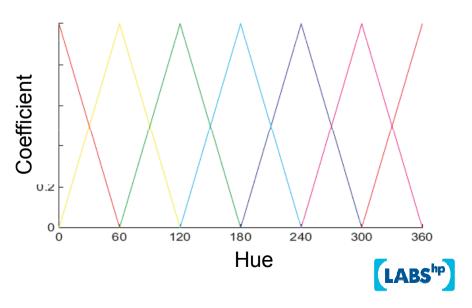


1. Colors similarity across histo bins is not considered:

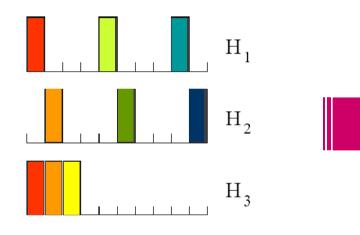


 $d(H_1, H_2) > d(H_1, H_3)$

- Cumulative histograms
- $d(H_1, H_2) = \sqrt{(H_1 H_2) \cdot A \cdot (H_1 H_2)^T}$
- Fuzzy histo



1. Colors similarity across histo bins is not considered:



 $d(H_1, H_2) > d(H_1, H_3)$

Cumulative histograms

•
$$d(H_1, H_2) = \sqrt{(H_1 - H_2) \cdot A \cdot (H_1 - H_2)^T}$$

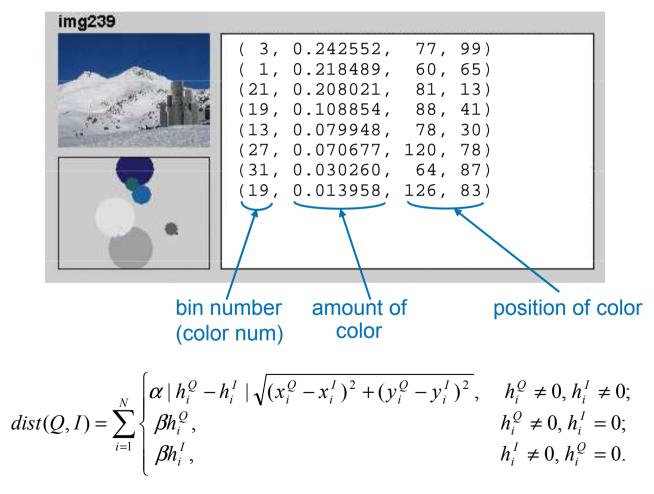
- Fuzzy histo
- Color similarity measure

$$\triangle E_{RGB} = \sqrt{\triangle R^2 + \triangle G^2 + \triangle B^2}$$

$$D_{cyl} = \sqrt{\Delta L^{*2} + C^{*}_{1}^{2} + C^{*}_{2}^{2} - 2C^{*}_{1}C^{*}_{2}\cos(\Delta H)}$$

(LABS^{hp})

2. Spatial color layout is not considered:



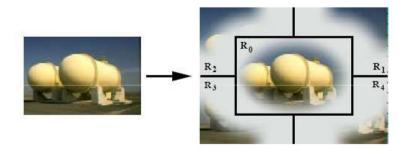
LABShp

Color moments

Average, standard deviation, skewness

$$E_{i} = \frac{1}{N} \sum_{j=1}^{N} p_{ij} \quad , \quad \sigma_{i} = \left(\frac{1}{N} \sum_{j=1}^{N} (p_{ij} - E_{i})^{2}\right)^{\frac{1}{2}} \quad \text{and} \quad s_{i} = \left(\frac{1}{N} \sum_{j=1}^{N} (p_{ij} - E_{i})^{3}\right)^{\frac{1}{3}}$$
$$d_{\text{mom}}(H, I) = \sum_{i=1}^{r} w_{i1} |E_{i} - F_{i}| + w_{i2} |\sigma_{i} - \varsigma_{i}| + w_{i3} |s_{i} - t_{i}|$$

- Average, covariance matrix of the color channels
- Consider spatial layout: fuzzy regions



Stricker M., Dimai A. Spectral Covariance and Fuzzy Regions for Image Indexing. Machine Vision and Applications, vol. 10., p. 66-73, 1997



Lecture 2: Outline

- Performance measurement
 - Retrieval effectiveness
- Some facts about human visual perception

Color features

- Color fundamentals
- Color spaces
- Color features: histograms and moments
- Comparison



Histograms or color moments? (1)



Stricker M., Orengo M. Similarity of Color Images. ... (3000 images)

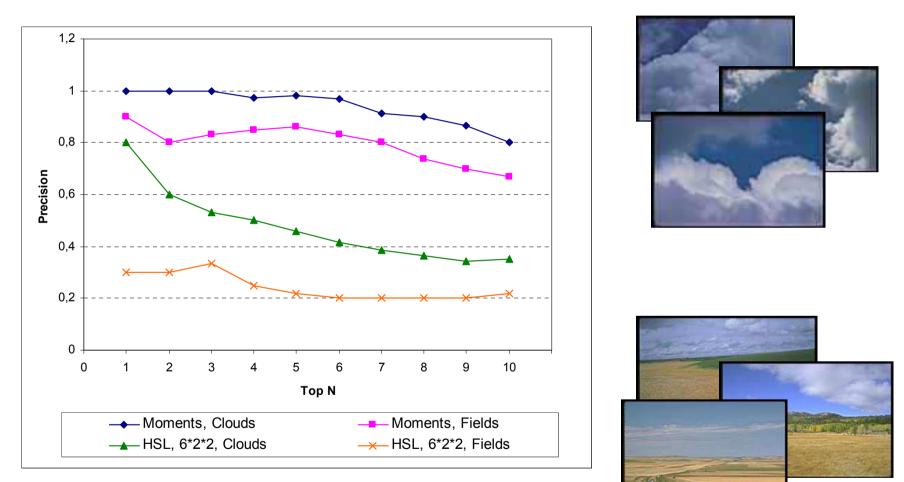
T			rank of the image			may
	index sim. mea	sure				max. rank
		W_1	4	5	8	8
	9 moments	W_2	2	8	6	8
		W_3	4	6	9	9
	8/2/2	L_{∞}	34	98	79	98
	16/4/4	L_{∞}	3	57	42	57
	cum. hist. $8/2/2$	L_1	53	162	30	162
	16/4/4	L_1	33	354	8	354
	8/2/2	L_2	65	158	34	158
	16/4/4	L_2	15	306	11	306
_	8/2/2	L_1	138	394	48	394
	16/4/4	L_1	4	132	6	132
	histogram $8/2/2$	L_2	71	541	102	541
_	16/4/4	L_2	10	1358	75	1358

Histograms or color moments? (2) ImageDB-1000

0,65 📥 HSL, Manhattan 0.8 HSL 17*12*15 0.6 📥 HSL, Cosine 0.7 0,55 0,5 Precision at N 0,6 Recall at 10 0,45 0.5 0,4 0,4 0,35 0.3 0.3 0.25 0.2 0.2 0,1 0,15 0 6*2*2 12*2*3 18*2*3 17*12*15 10 0 2 9 3 5 Quantization Top N

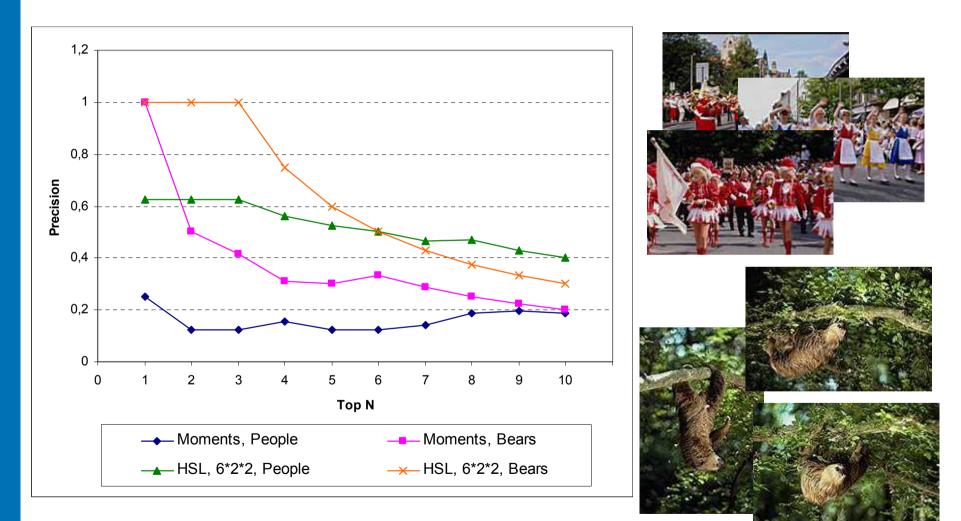
LABS^{hp}

Histograms or color moments? (3)





Histograms or color moments? (4)



(LABS^{hp})

Lecture 2: Resume

- Performance: efficiency and effectiveness
 - Lack of the common benchmark collections and retrieval effectiveness measurement
- Human visual perception is very complex
 - Have to take into account known facts about our perception to reduce the semantic gap
- Color features: histograms and moments
 - On heterogeneous collections moments are slightly better
 - Fusion of histograms and moments can give better results



Lecture 2: Bibliography

- Muller H., Muller W., McG. Squire D., Marchand-Maillet S., Pun T. Performance evaluation in content-based image retrieval: overview and proposals. In Pattern Recognition Letters, vol. 22, pp. 593-601, 2001.
- Lu G., Sajjanhar A. On performance measurement of multimedia information retrieval systems. In Proc of the International Conference on Computational Intelligence and Multimedia Applications, pp.781-787, 1998.
- Swain M. J., Ballard D. H. Color indexing. In International Journal of Computer Vision, vol. 7, no. 1, pp. 1132, 1991.
- Stricker M., Orengo M. Similarity of Color Images. In Proc. of the SPIE Conference, vol. 2420, pp. 381 – 392, 1995.
- Stricker M., Dimai A. Spectral Covariance and Fuzzy Regions for Image Indexing. In Machine Vision and Applications, vol. 10, pp. 66 – 73, 1997.
- Sarifuddin M., Missaoui R. A new perceptually uniform color space with associated color similarity measure for content based image and video retrieval. In Proc. of the ACM SIGIR Workshop on Multimedia Information Retrieval, 2005.
- Sural S., Qian G., Pramanik S. A histogram with perceptually smooth color transition for image retrieval. In Proc. of the Fourth International Conference on Computer Vision, Pattern Recognition and Image Processing, 2002.

