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State of the art in color image processing and analysis

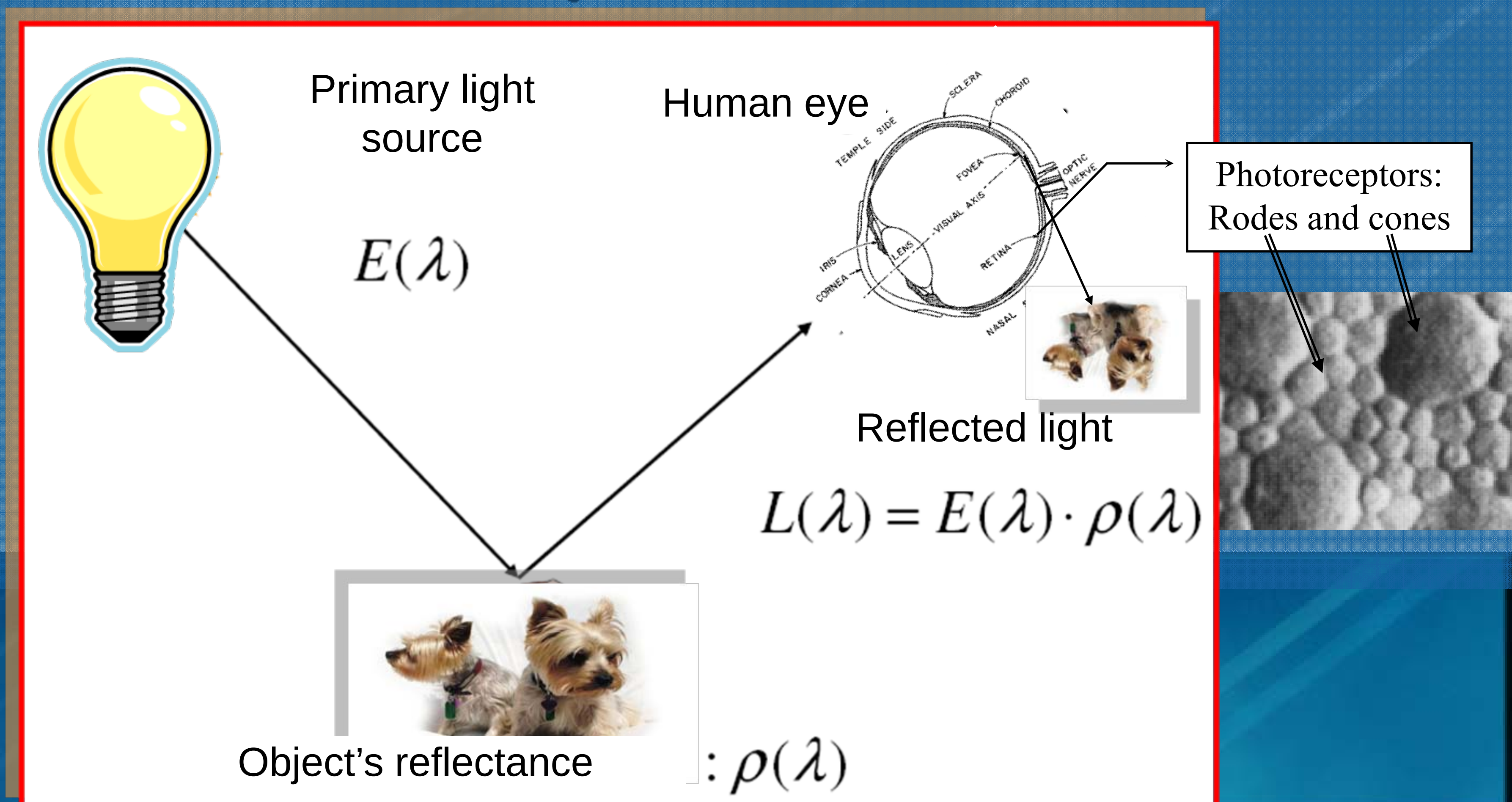
Presentation contents

1. Human perception of color images (1)

- **Perception of color** – crucial for many machine vision applications
- **General observation:**
  - most color image processing algorithms consider one pixel at a time,
  - **but in the HVS – the color perceived at a spatial location is influenced by the color of all the spatial locations in the field of view!**
- **Future issues for color image processing:** use the human visual models to describe ***the color appearance of spatial information,*** to replace the common low level (pixel-level) approaches => future trends: ***develop color image processing and analysis algorithms based on high level concepts***

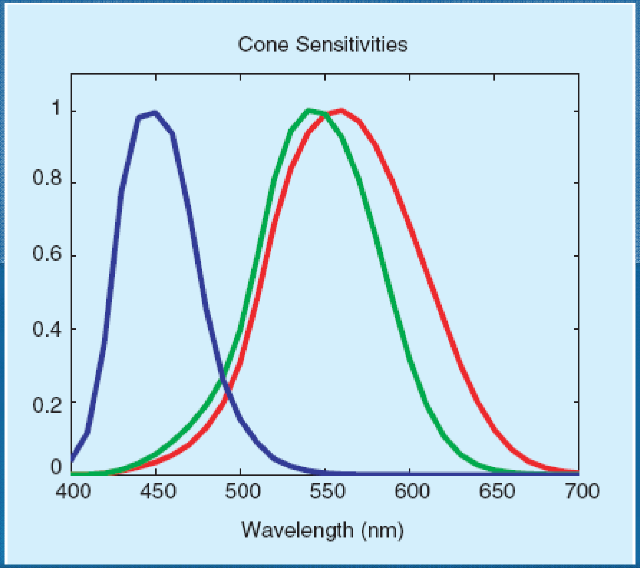
1. Human perception of color images (2)

- **The human color vision system:**



1. Human perception of color images (3)

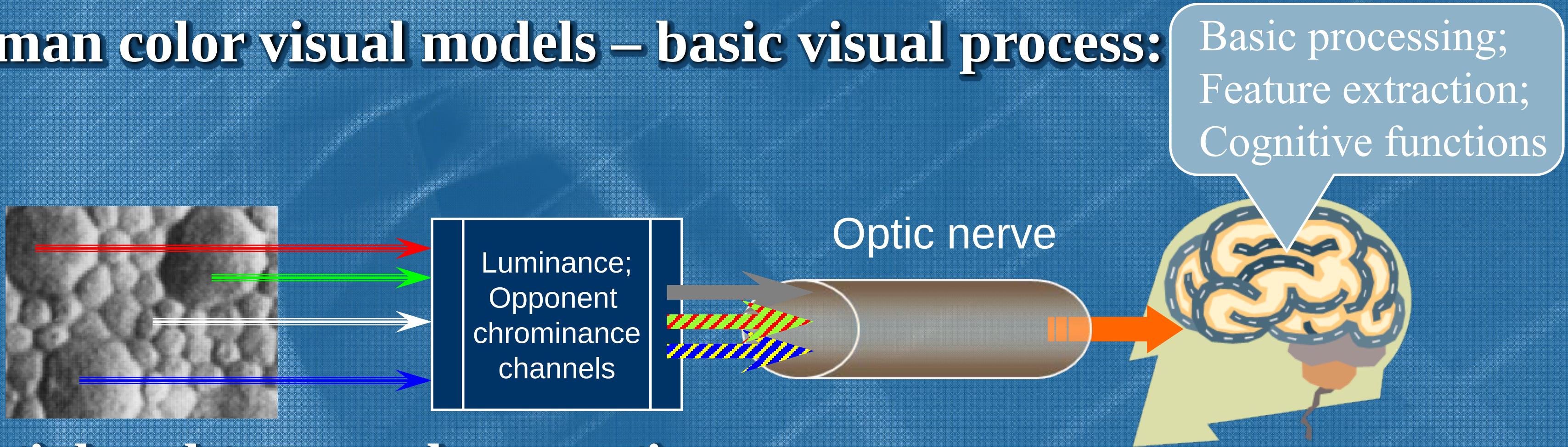
- **Photoreceptors in retina:**
  - **Rods** = sensitive to low levels of light; can't perceive color
    = absent in the fovea; maximum density in 18^0 eccentricity annulus
    => "peripheral vision field"
  - **Cones** = sensitive to normal light level (daylight); perceive color
    = 3 types of cones: long (L), medium (M), short (S) wavelength
    = maximum density in **fovea** ("central visual field", 2^0 eccentricity)



- **Types of vision (visual response):**
  - **Scotopic vision**
    = monochromatic vision
    = rods only active below 0.01 cd/m^2
  - **Photopic vision**
    = color vision
    = cones only active above 10 cd/m^2
  - **Mesopic vision** => rods and cones active

1. Human perception of color images (4)

- **Human color visual models – basic visual process:**



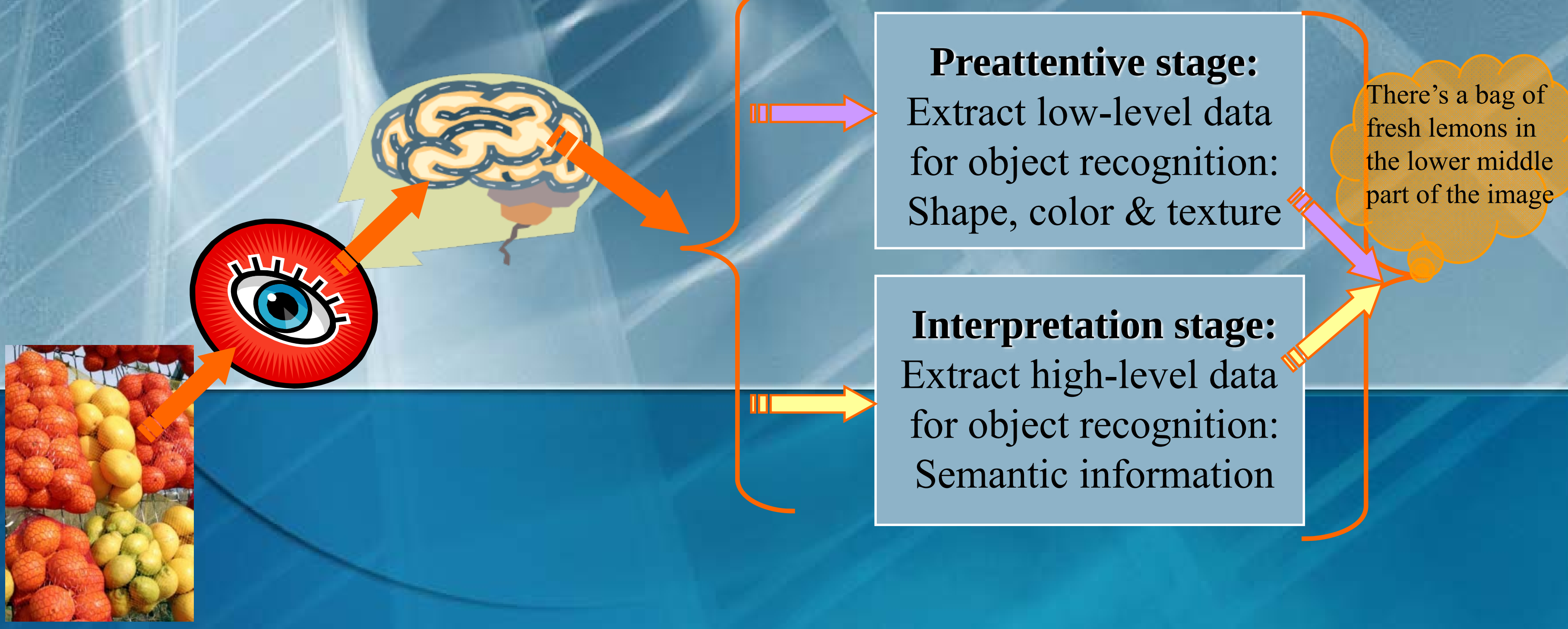
- **Spatial and temporal perception:**
  - **Visual info – simultaneously processed in several "visual channels":**
    - **high frequency active channels** (P-channels): perception of details
    - **medium frequency active channels**: shape recognition
    - **low frequency active channels** (M-channels): perception of motion

=> The simultaneous results of the 3 channels, achromatic & chromatic,

- filtered by specific spatial and temporal contrast sensitivity functions (CSFs); achromatic CSF > chromatic CSF
- combined further in the vision process

1. Human perception of color images (5)

- **Human color visual model – a point of view:**
  - Still an open research issue; gap between traditional computer vision and human vision sciences => **new human vision models needed**
  - **The mixed image-based and learning-based model approach:**



2. Color imaging applications - overview

I. Consumer imaging applications:

- **Mostly involves image processing, image enhancement**
- **Color management challenges** => achieve WYSIWYG concept, by color appearance models & color management methods – standardized
- **Basic applications fields**: graphics arts; HDTV; web; cinema; archiving, involving image/video restoration, colorization, image inpainting

II. Medical imaging applications:

- **Mostly involves image analysis**
- **Challenges** => model image formation process & correlate image interpretation with physics based models;
  => analyze changes over time
- **Methods**: use low level features & add high level interpretation to assist diagnostic

III. Machine vision applications:

- Robot vision; industrial inspection => **image analysis & interpretation methods – similar to medical imaging**

3. Color spaces, properties, metrics (1)

- **Color spaces properties:**

- **P1. Completeness:**

  Def.1: A color space S_C is called ***visually complete*** iff includes all the colors perceived as distinct by the eye

  Def.2: A color space S_C is called ***mathematically complete*** iff includes all the colors possible to appear in the visible spectrum

- **P2. Compactness:**

  Def.: A color space S_C is called ***compact*** if any two points of the space $\mathbf{s_i}$, $\mathbf{s_j}$ are perceived as distinct colors

  - Note: One can obtain a compact color space from a mathematically complete color space through color space quantization (e.g.: vector quantization)

3. Color spaces, properties, metrics (2)

- **P3. Uniformity:**

  Def.1: A color space S_C is called ***uniform*** if a distance norm d_C over S_C can be defined so that: $d_C(\mathbf{s_i}, \mathbf{s_j})$ ~ perceptual similarity of $\mathbf{s_i}$ and $\mathbf{s_j}$

  - **Note:** Usually, d_C = Euclidian distance

- **P4. Naturalness:**

  Def.: The color space S_C is called ***natural*** if its coordinates are directly correlated to the perceptual attributes of color.

  The perceptual attributes of color = the HVS specific attributes in the perception and description of a color: ***Brightness; Nuance (Hue); Saturation (Purity).***

  - **Note:** the RGB space (the primary color space) only satisfies completeness => the need to define other spaces for color representation.

3. Color spaces, properties, metrics (3)

- **Conventional color spaces:**
  - Reversible transforms of the primary (RGB) color space
  - Classified as linear and non-linear
  - **Linear transforms to obtain color spaces =** rotations and scalings of the RGB cube (OPP, YUV, YIQ, YCbCr, XYZ, Ohta $I_1I_2I_3$ …)

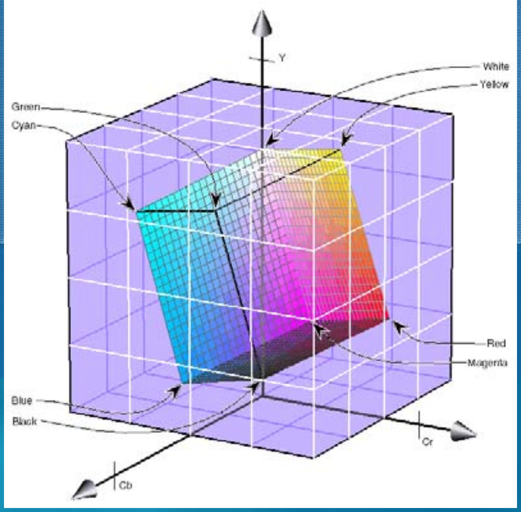
$$\mathbf{s}_{(C)} = \mathbf{T}^{(C)}\mathbf{s}, \quad \forall \mathbf{s} \in S_{(R,G,B)}.$$

$$\mathbf{s} = \left(\mathbf{T}^{(C)}\right)^{-1}\mathbf{s}_{(C)}, \quad \forall \mathbf{s}_{(C)} \in S^{(C)}.$$

$$\mathbf{T}^{(OPP)} = \begin{bmatrix} 1 & 1 & 1 \\ -1 & -1 & 2 \\ 1 & -2 & 1 \end{bmatrix}; \quad \mathbf{T}^{(YUV)} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.1 \end{bmatrix}; \quad \mathbf{T}^{(YIQ)} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix}.$$

$$\mathbf{T}^{(YCrCb)} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.5 & -0.4187 & -0.0813 \\ -0.1687 & -0.3313 & 0.5 \end{bmatrix}. \quad \mathbf{T}^{(XYZ)} = \begin{bmatrix} 0.49 & 0.31 & 0.2 \\ 0.177 & 0.812 & 0.011 \\ 0 & 0.01 & 0.99 \end{bmatrix}.$$

$$\mathbf{T}^{(I_1I_2I_3)} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 0 & -1/2 \\ -1/4 & 1/2 & -1/4 \end{bmatrix}.$$



3. Color spaces, properties, metrics (4)

- **Conventional color spaces (2):**
  - **Non-linear transforms to obtain color spaces =>** needed to match the perceptual color attributes by their coordinates (CIE L*a*b*, CIE L*u*v*, HSV, HLS, HSI, Munsell.

$$H=\begin{cases}\theta & \text{if } B\le G\\ 360-\theta & \text{if } B>G\end{cases}\quad \text{with } \theta=\cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{\frac{1}{2}}}\right\}$$

$$S=1-\frac{3}{(R+G+B)}[\min(R,G,B)]$$

$$I=\frac{1}{3}[R+G+B]$$

$$L^* = 116 f\left(\frac{Y}{Y_0}\right) - 16$$
$$a^* = 500\left[f\left(\frac{X}{X_0}\right) - f\left(\frac{Y}{Y_0}\right)\right]$$
$$b^* = 200\left[f\left(\frac{Y}{Y_0}\right) - f\left(\frac{Z}{Z_0}\right)\right]$$

$$f(x)=\begin{cases}x^{\frac{1}{3}}, & x>0.008856\\ 7.787x+\frac{16}{116} & \text{otherwise,}\end{cases}$$

RG sector ($0 \le H < 120$)

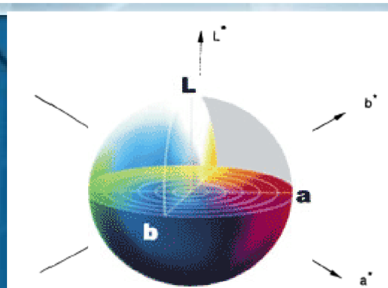
$$B=I(1-S)$$
$$R=I\left[1+\frac{S\cos H}{\cos(60-H)}\right]$$
$$G=1-(R+B)$$

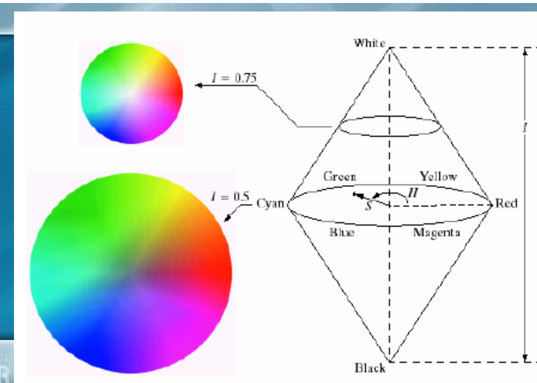
GB sector ($120 \le H < 240$)

$$R=I(1-S)$$
$$G=I\left[1+\frac{S\cos(H-120)}{\cos(60-(H-120))}\right]$$
$$B=1-(R+G)$$

BR sector ($240 \le H < 360$)

$$G=I(1-S)$$
$$B=I\left[1+\frac{S\cos(H-240)}{\cos(60-(H-240))}\right]$$
$$R=1-(G+B)$$





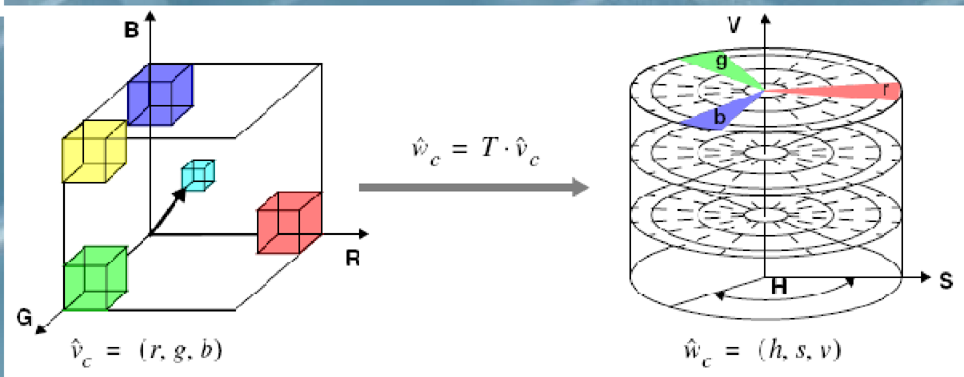
3. Color spaces, properties, metrics (5)

- Denote: r, g, b – color primaries normalized to [0;1]
  => HSV space transformations:

$$\mathbf{v} = \max(r, g, b), \qquad \mathbf{s} = \frac{\mathbf{v} - \min(r, b, g)}{\mathbf{v}}$$

$$\acute{r} = \frac{\mathbf{v} - r}{\mathbf{v} - \min(r, b, g)}, \quad \acute{g} = \frac{\mathbf{v} - g}{\mathbf{v} - \min(r, b, g)}, \quad \acute{b} = \frac{\mathbf{v} - b}{\mathbf{v} - \min(r, b, g)}$$

$$6\mathbf{h} = \begin{cases} 5 + \acute{b} & \text{if } r = \max(r,g,b) \text{ and } g = \min(r,b,g) \\ 1 - \acute{g} & \text{if } r = \max(r,g,b) \text{ and } g \neq \min(r,b,g) \\ 1 + \acute{r} & \text{if } g = \max(r,g,b) \text{ and } b = \min(r,b,g) \\ 3 - \acute{b} & \text{if } g = \max(r,g,b) \text{ and } b \neq \min(r,b,g) \\ 3 + \acute{g} & \text{if } b = \max(r,g,b) \text{ and } r = \min(r,b,g) \\ 5 - \acute{r} & \text{otherwise} \end{cases}$$



Reverse transform:

$$\alpha = 6\mathbf{h} - \mathrm{round}(6\mathbf{h}), \qquad \omega_1 = (1 - \mathbf{s}) * \mathbf{v},$$
$$\omega_2 = (1 - (\mathbf{s} * \alpha)) * \mathbf{v}, \qquad \omega_3 = (1 - (\mathbf{s} * (1 - \alpha))) * \mathbf{v}$$

$$\mathbf{r} = \begin{cases} \mathbf{v} & \text{if } \alpha = 0 \text{ or } \alpha = 5 \\ \omega_1 & \text{if } \alpha = 2 \text{ or } \alpha = 3 \\ \omega_2 & \text{if } \alpha = 1 \\ \omega_3 & \text{if } \alpha = 4 \end{cases} \qquad \mathbf{g} = \begin{cases} \mathbf{v} & \text{if } \alpha = 1 \text{ or } \alpha = 2 \\ \omega_1 & \text{if } \alpha = 4 \text{ or } \alpha = 5 \\ \omega_2 & \text{if } \alpha = 3 \\ \omega_3 & \text{if } \alpha = 0 \end{cases} \qquad \mathbf{b} = \begin{cases} \mathbf{v} & \text{if } \alpha = 3 \text{ or } \alpha = 4 \\ \omega_1 & \text{if } \alpha = 0 \text{ or } \alpha = 1 \\ \omega_2 & \text{if } \alpha = 5 \\ \omega_3 & \text{if } \alpha = 2 \end{cases}$$

3. Color spaces, properties, metrics (6)

- **Ad-hoc color spaces:**
  - Ideea: define the color space according to the ***most characteristic color components of a set of images*** ⇔ application-dependent
    => e.g. YST color space for human faces: Y – luminance; S – color average value from the set of faces; T – the orthogonal to Y and S
  - **Some basic approaches:**

    (1) For image segmentation:

    Fischer distance strategy to segment object-background (LDA generated color space)

    (2) For feature detection:

    Diversification principle strategy for selection & fusion of color components => automatically weight color components to balance between color invariance & discriminative power

    (3) For object tracking:

    Adaptive color space switching strategy => dinamically select the best color space for given environment lighting (from all conventional color spaces)

3. Color spaces, properties, metrics (7)

- **Color difference metrics in color spaces:**
  - **In linear transformed-based color spaces =>** Euclidian metric – common choice
  - **In non-linear transformed based spaces =>** metrics should take into account what is linear and what is angular! (i.e. see hue! – an angle)
  - **Some basic metrics:**

    (1) Variants of Euclidian distance for linear spaces:

    Minkowski distance (q=1 – city-block; q=2 – Euclidian):

$$d(i,j)=\sqrt[q]{(|x_{i_1}-x_{j_1}|^q+|x_{i_2}-x_{j_2}|^q+\ldots+|x_{i_p}-x_{j_p}|^q)}$$

    Mahalanobis distance:

$$mahalanobis(x,y)=\sqrt{(x-y)\Sigma^{-1}(x-y)^T}$$

3. Color spaces, properties, metrics (8)

- **Color difference metrics in color spaces – contnd.:**

(2) CIEDE2000:

defined for CIELAB space:

$$\Delta E_{00}(L_1^*, a_1^*, b_1^*; L_2^*, a_2^*, b_2^*) = \Delta E_{00}^{12} = \Delta E_{00}$$

$$\begin{aligned}
C_{i,ab}^* &= \sqrt{(a_i^*)^2 + (b_i^*)^2} \qquad i = 1,2 \\
\bar{C}_{ab}^* &= \frac{C_{1,ab}^* + C_{2,ab}^*}{2} \\
G &= 0.5\left(1 - \sqrt{\frac{\bar{C}_{ab}^{*\,7}}{\bar{C}_{ab}^{*\,7} + 25^7}}\right) \\
a_i' &= (1+G)a_i^* \qquad i = 1,2 \\
C_i' &= \sqrt{(a_i')^2 + (b_i^*)^2} \qquad i = 1,2 \\
h_i' &= \begin{cases} 0 & b_i^* = a_i' = 0 \\ \tan^{-1}(b_i^*, a_i') & \text{otherwise} \end{cases} \qquad i = 1,2
\end{aligned}$$

$$\begin{aligned}
\Delta L' &= L_2^* - L_1^* \\
\Delta C' &= C_2' - C_1' \\
\Delta h' &= \begin{cases} 0 & C_1'C_2' = 0 \\ h_2' - h_1' & C_1'C_2' \neq 0;\ |h_2' - h_1'| \leq 180^\circ \\ (h_2' - h_1') - 360 & C_1'C_2' \neq 0;\ (h_2' - h_1') > 180^\circ \\ (h_2' - h_1') + 360 & C_1'C_2' \neq 0;\ (h_2' - h_1') < -180^\circ \end{cases} \\
\Delta H' &= 2\sqrt{C_1'C_2'}\sin\left(\frac{\Delta h'}{2}\right) \\
\bar{L}' &= (L_1^* + L_2^*)/2 \\
\bar{C}' &= (C_1' + C_2')/2
\end{aligned}$$

3. Color spaces, properties, metrics (9)

$$
\begin{aligned}
\bar{h}' &= \begin{cases} \frac{h_1'+h_2'}{2} & |h_1'-h_2'| \leq 180^\circ; C_1'C_2' \neq 0 \\ \frac{h_1'+h_2'+360^\circ}{2} & |h_1'-h_2'| > 180^\circ; (h_1'+h_2') < 360^\circ; C_1'C_2' \neq 0 \\ \frac{h_1'+h_2'-360^\circ}{2} & |h_1'-h_2'| > 180^\circ; (h_1'+h_2') \geq 360^\circ; C_1'C_2' \neq 0 \\ (h_1'+h_2') & C_1'C_2' = 0 \end{cases} \\
T &= 1 - 0.17\cos(\bar{h}' - 30^\circ) + 0.24\cos(2\bar{h}') \\
&\quad +0.32\cos(3\bar{h}' + 6^\circ) - 0.20\cos(4\bar{h}' - 63^\circ) \\
\Delta\theta &= 30\exp\left\{-\left[\frac{\bar{h}' - 275^\circ}{25}\right]^2\right\} \\
R_C &= 2\sqrt{\frac{\bar{C}'^7}{\bar{C}'^7 + 25^7}} \\
S_L &= 1 + \frac{0.015(\bar{L}' - 50)^2}{\sqrt{20 + (\bar{L}' - 50)^2}} \\
S_C &= 1 + 0.045\bar{C}' \\
S_H &= 1 + 0.015\bar{C}'T \\
R_T &= -\sin(2\Delta\theta)R_C \\
\Delta E_{00}^{12} &= \Delta E_{00}(L_1^*, a_1^*, b_1^*; L_2^*, a_2^*, b_2^*) \\
&= \sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T\left(\frac{\Delta C'}{k_C S_C}\right)\left(\frac{\Delta H'}{k_H S_H}\right)}
\end{aligned}
$$

4. Basic color image processing

- **Important note: Color image processing is not merely the processing of 3 monochrome channels!!!**

- **Yet => some generalizations and applications of monochrome (grey-level) image processing can be derived/used in color image processing and analysis:**

    - **Generalization of scalar algorithms to the vectors case (color space)**
    - **Processing of the luminance (brightness) component alone**
    - **Independent & different processing of each coordinate, after the color space transform** (linear or non-linear transform)

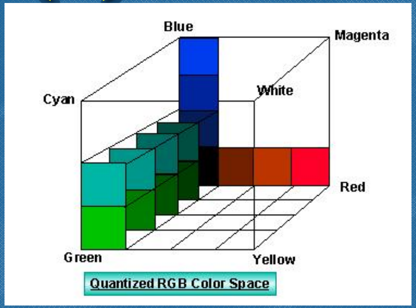
4.1. Color image quantization (1)

- **Goal of quantization:** build a reduced color space, with the smallest possible number of colors (the representative image colors), so that the perceived difference between the quantized image and original image → 0.

- **Open problem:** definition of "perceived difference";
  - 1st approach: minimize the sum of distances between colors and the centers of color clusters resulting in the quantization process (⇔ minimize the sum of distances within each cluster)
  - 2nd approach: maximize the sum of distances between the colors in different clusters (⇔maximize the sum of distances between cluster pairs)

- **Typical approach for color space quantization: VQ**

4.1. Color image quantization (2)

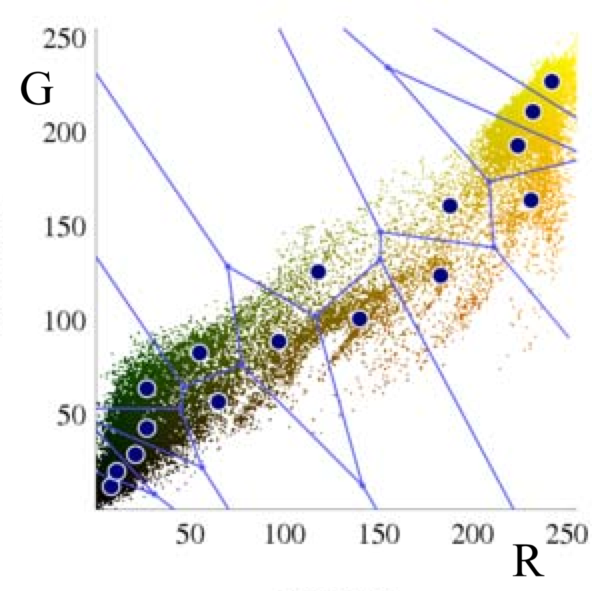


- **Vectorial Quantization (VQ) of the color space:**
  - Several versions; all based on LBG original algorithm
  - Motivation: reduce (usually drastically!) the number of colors in a group of images. How? **Cluster** similar colors together (color points = vectors => the name "***vector quantization***" = ***VQ***); determine the **cluster centers**; replace each image color with the closest cluster center

B=0 for all pixels

VQ codebook

(Voronoi diagram)



4.1. Color image quantization (3)

- **Vectorial Quantization (VQ) of the color space – basic algorithm:**
  - Let: N – # of colors in the (set of) image (s); M – target number of colors ($M \ll N$); each color = $\mathbf{s}_i[3 \quad 1]$ (e.g. $\mathbf{s}_i=[R\ G\ B]^T$), $i=1,2,...,M$ clusters
  - **Algorithm:**

    1. **Initialization:** choose M "codewords", $\{\mathbf{s}_{q1}, \mathbf{s}_{q2},..., \mathbf{s}_{qM}\}$ lying in the color space chosen for quantization ⇔ *codeword initialization*
    2. **Codebook optimization:**

       2.1. For each $i=1,2,...,M$, assign $\mathbf{s}_i$ to the cluster k that satisfies:

       $$k = \arg\min_{j=1,2,...,M} d(\mathbf{s}_i, \mathbf{s}_{qj})$$

       => The initial partition regions = the initial clusters $B_1, B_2,...,B_M$.

       2.2. Compute the overall distortion:

       $$D = \frac{1}{N}\sum_{j=1}^{M}\sum_{\mathbf{s}_i \in B_j} d(\mathbf{s}_i, \mathbf{s}_{qj})$$

       2.3. If $D>\varepsilon$ => update codewords: $\mathbf{s}_{qj} = \frac{1}{card(B_j)}\sum_{\mathbf{s}_i \in B_j}\mathbf{s}_i$

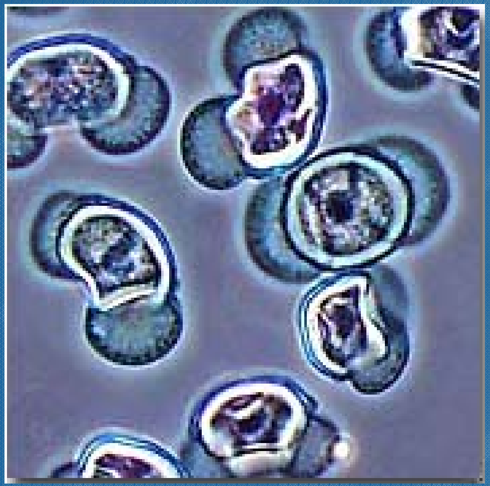
       and go to step 2. Otherwise => convergence reached => final codebook and codewords.

4.2. Color image filtering (1)

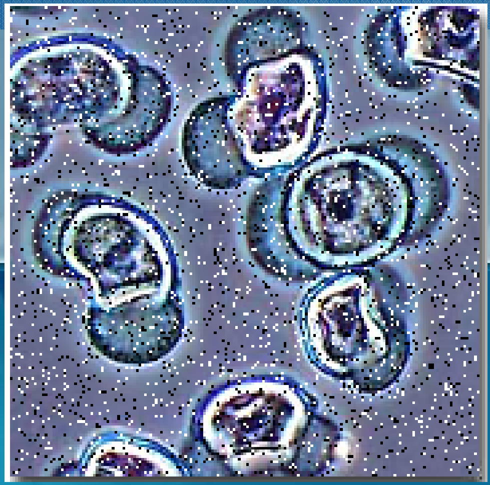
- **Most popular filtering goal :** remove noise (color noise) from the original
- Why is noise disturbing?
  - **Perceptually:** image appearing visually unpleasant,...
  - **For analysis applications:** noise = high frequency => same as sharp edges...
- **Noise filtering** algorithms for **color images**:
  - Most common types of noise: impulse noise; Gaussian noise; speckle noise; stripping noise
  - Several types of vector filtering operators derived in last 10 years
  - Important class of noise filtering operators for color images: rank vector filters
  - Open issues: **develop adaptive filters for color images,** to preserve fine details & reduce all types of noise efficiently (including additive!) ⇔ filters capable to **adapt to local image statistics!**
  - Other filtering approaches: morphological operators; wavelets; PDEs...

4.2. Color image filtering (2)

- **Vector median filters for color images:**
  - Particular case of rank filters
  - Principle: for each pixel location (i, j):
    - take the brightness/color values in a window $W_{(i,j)}$
    - order the brightness/color values in increasing order
    - output: new brightness/color at (i, j) = middle of string
  - Very useful for impulse color noise:

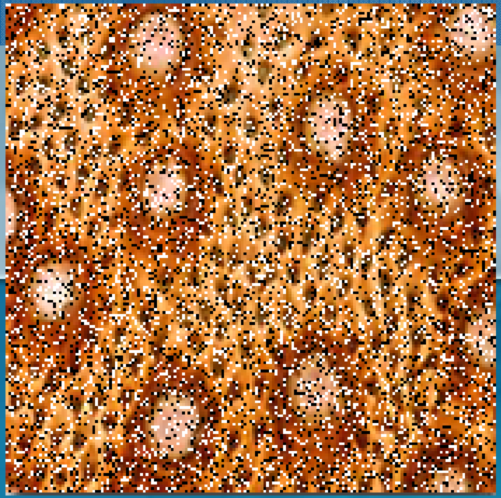


Original (noise-free)



10% impulse noise

Original (noise-free)



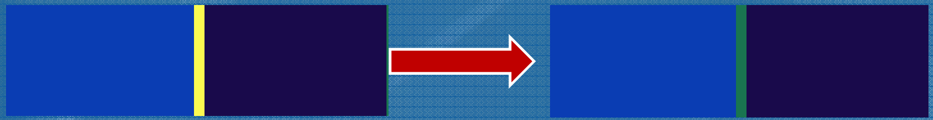
30% impulse noise

4.2. Color image filtering (3)

- **Vector median filters for color images** – some practical algorithms:

Note:

- o Biggest problem in vector median filtering generalization for color images: (1) **how** to define the ordering?; (2) **what** means "increasing color values"?
- o "Brute approach" (i.e. in RGB space => treat each channel independently, apply 3 median filters independently) **does not work!** (color distortion): 3 1 window, $\mathbf{s}_1$=[7 117 182], $\mathbf{s}_2$=[250 250 80], $\mathbf{s}_3$=[25 10 75]=> filter independently: **s**=[25 117 80]...



=> solutions:

1. The Adaptive Scalar Median Filter:

- Consider 2 representations of the image: in RGB and HSI color space => denote: $\mathbf{s}_p=[R\ G\ B]^T$; $\mathbf{s}_h=[h\ s\ i]^T$
- W – any window around the current pixel (x,y); e.g. $W_{(x,y)}[3\ \ 3]$.
- Let: r_m, g_m, b_m – average R, G, B values inside $W_{(x,y)}$;
- Compute: $[h_m\ s_m\ i_m]^T = \mathrm{HSI}([r_m\ g_m\ b_m]^T)$;

4.2. Color image filtering (4)

- Additional : (x_R,y_R) = pixel position in $W_{(x,y)}$ that satisfies:
  $R(x_R,y_R)=\text{median}\{R(x,y)|(x,y) \text{ in } W_{(x,y)}\}$
  (x_G,y_G) = pixel position in $W_{(x,y)}$ that satisfies:
  $G(x_G,y_G)=\text{median}\{G(x,y)|(x,y) \text{ in } W_{(x,y)}\}$
  (x_B,y_B) = pixel position in $W_{(x,y)}$ that satisfies:
  $B(x_B,y_B)=\text{median}\{B(x,y)|(x,y) \text{ in } W_{(x,y)}\}$

$\Rightarrow$ **We can now build a "median matrix" M**[3×3]:

$$\mathbf{M} = \begin{bmatrix} R(x_R,y_R) & R(x_G,y_G) & R(x_B,y_B) \\ G(x_R,y_R) & G(x_G,y_G) & G(x_B,y_B) \\ B(x_R,y_R) & B(x_G,y_G) & B(x_B,y_B) \end{bmatrix}$$

- ***Note:***
  - o The diagonal of **M** – most likely to be the median color, ***but*** is a ***new color!!!***
  - o Any column of **M** = an existing color , **but** not necessarily really the median!
  - o **=> *Virtually*** one can select as filter's output ***any*** combination of RGB values => how do we know which one is ***optimal?***

4.2. Color image filtering (5)

- ***Selection criteria*** for the output color of the adaptive scalar median filter:

C1. The hue changes should be minimized
C2. The shift of saturation should be as small as possible.
C3. An increase in saturation is preferable to a decrease in saturation
C4. Maximize the relative luminance contrast.

⇒ ***In mathematical (algorithmical) form:***

1. Find (l,p,q) so that:

$$\left| HSI\left(\left[\mathbf{M}(1,l)\,\mathbf{M}(2,p)\,\mathbf{M}(3,q)\right]\right)(1) - h_m \right| = \left| h(l,p,q) - h_m \right| = \min_{(i,j,k)\in\{1,2,3\}^3} \left| h(i,j,k) - h_m \right|$$

2. If (l,p,q) is unique => output = $[\mathbf{M}(1,l)\ \mathbf{M}(2,p)\ \mathbf{M}(3,q)]^T$; ***otherwise:*** on the subset of (l,p,q) candidates, find (l',p',q') so that:

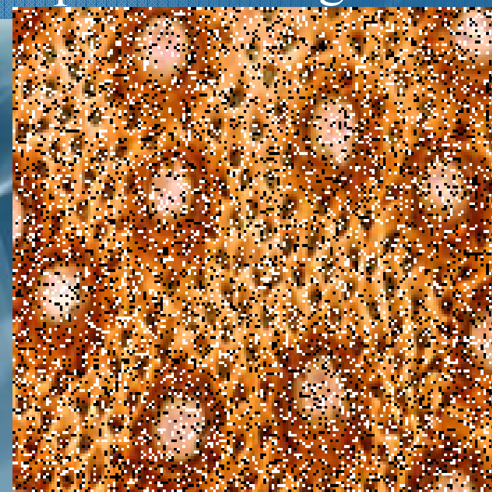
$$\left| HSI\left(\left[\mathbf{M}(1,l')\,\mathbf{M}(2,p')\,\mathbf{M}(3,q')\right]\right)(2) - s_m \right| = \left| s(l',p',q') - s_m \right| = \min_{(i,j,k)\in\{(l,p,q)\}} \left| s(i,j,k) - s_m \right|$$

3. If (l',p',q') is unique => output = $[\mathbf{M}(1,l')\ \mathbf{M}(2,p')\ \mathbf{M}(3,q')]^T$; ***otherwise:*** on the subset of (l',p',q') candidates, select the one with largest s and i.

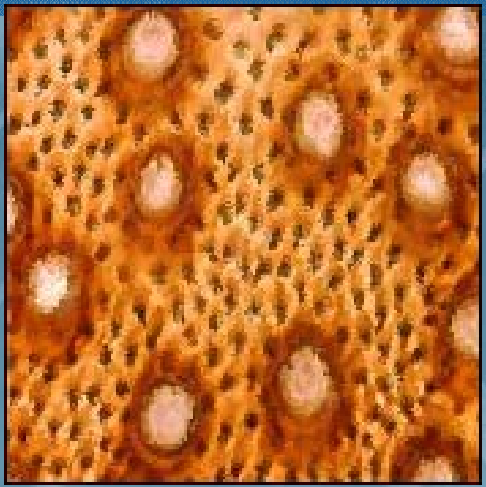
4.2. Color image filtering (6)

- Results of scalar adaptive filtering:

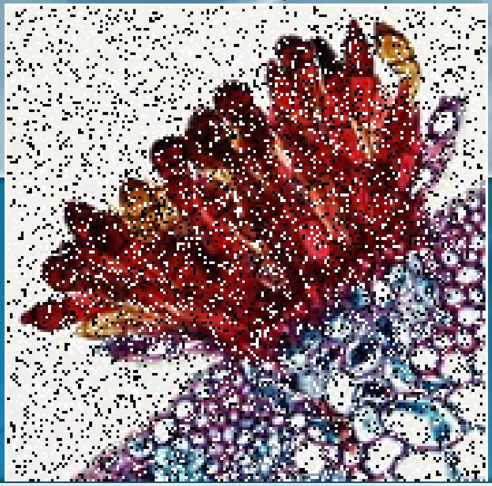
original



noisy



filtered



4.2. Color image filtering (7)

2. The Vector Median Filter:

- Unlike the scalar adaptive median filter => it ***guarantees*** that its output = ***always a color that is present in the image window***
- Consider the RGB color space representation of the image, $\mathbf{s}=[R\ G\ B]^T$;
- W – any window around the current pixel (x,y); e.g. $W_{(x,y)}[3\ \ 3]$.
- $\|\bullet\|_L$ – some vector norm (e.g. Euclidian distance)
- Let: $\{\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N\}$= the colors inside $W_{(x,y)}$ => the ***vector median filter:***

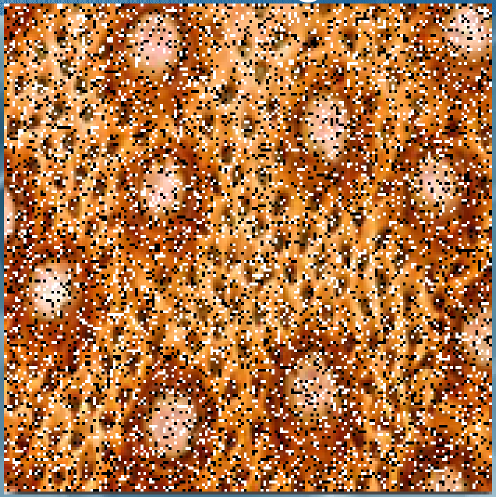
$$VM\{\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N\} = \mathbf{s}_{VM}, \quad \mathbf{s}_{VM} \in \{\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N\}$$

so that:

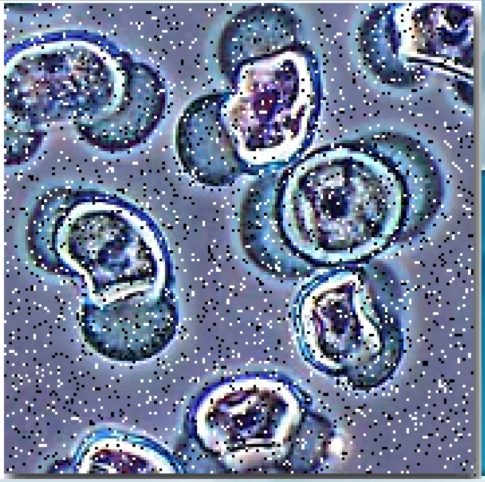
$$\sum_{i=1}^{N} \left\| \mathbf{s}_{VM} - \mathbf{s}_i \right\|_L \leq \sum_{i=1}^{N} \left\| \mathbf{s}_j - \mathbf{s}_i \right\|_L, \ \forall j = 1,2,\ldots,N.$$

4.2. Color image filtering (8)

- Results of vector median filtering:


original | noisy | filtered


4.2. Color image filtering (9)

2. The Median Filter Based on Conditional Ordering in the HSV Space :

- Consider the representation of the image in HSV color space => denote: $\mathbf{s}=[h\ s\ v]^T$, h – angle, s,v – [0;1] valued
- W – any window around the current pixel (x,y); e.g. $W_{(x,y)}[3\ \ 3]$.
- Principle of the conditional ordering based filter:
  - (1) select a-priori an *importance order* for the vectors' components
  - (2) order the vectors based on their components' relation in the predefined order

- In the HSV color space: conditional ordering based filtering principles:
  (1) sort the color vectors in W based on v: order from smallest to largest v
  (2) ***ordering colors with same v***: sort based on s: from largest to smallest s
  (3) ***ordering colors with same v and s:*** from smallest to largest h

4.2. Color image filtering (10)

⇒ **Define the operators:** $<_{hsv}$,$=_{hsv}$ **for color ordering in the HSV color space** as follows:

if: $\mathbf{s}_1 = [h_1 \quad s_1 \quad v_1]^T ; \mathbf{s}_2 = [h_2 \quad s_2 \quad v_2]^T$ = 2 colors in HSV,

then:

$$\mathbf{s}_1 <_{hsv} \mathbf{s}_2 \Leftrightarrow ((v_1 < v_2) \vee ((v_1 = v_2) \wedge (s_1 > s_2)) \vee ((v_1 = v_2) \wedge (s_1 = s_2) \wedge (h_1 < h_2)))$$

$$\mathbf{s}_1 =_{hsv} \mathbf{s}_2 \Leftrightarrow ((v_1 = v_2) \wedge (s_1 = s_2) \wedge (h_1 = h_2))$$

⇒ Let: $\{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_N\}$= the colors inside $W_{(x,y)}$=>the HSV conditional ordering median filter algorithm:

1. Order $\{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_N\}$ increasingly in respect to $<_{hsv}$:

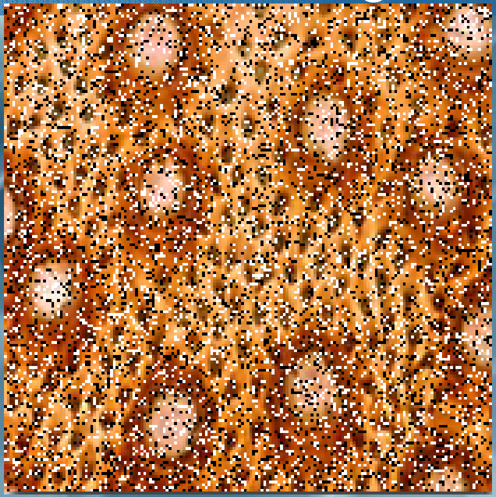
$$\{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_N\} \rightarrow \{\mathbf{s}'_1, \mathbf{s}'_2, ..., \mathbf{s}'_N\}, \forall \mathbf{s}'_i \in \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_N\}, \mathbf{s}'_1 <_{hsv} \mathbf{s}'_2 ... <_{hsv} \mathbf{s}'_N$$

2. Output the color in the middle of the ordered strig: med$\{\mathbf{s}'_1, \mathbf{s}'_2, ..., \mathbf{s}'_N\}$

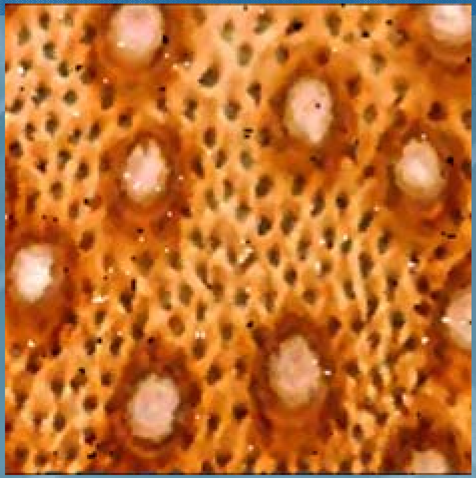
4.2. Color image filtering (11)

- Results of HSV conditional ordering median filter:

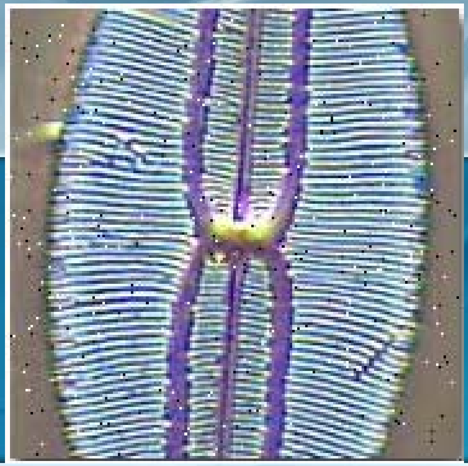
original

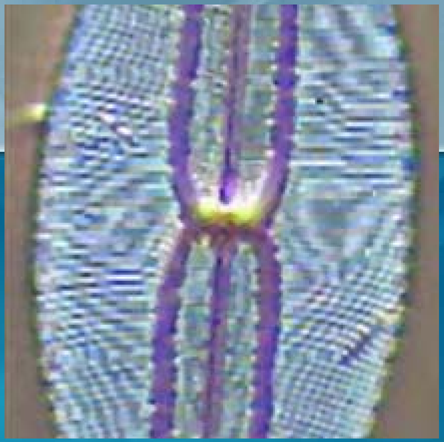


noisy



filtered





4.3. Color image enhancement (1)

- **Can have various goals** (more than grey level image enhancement) ; some typical:

1. Image contrast enhancement
2. Color enhancement ⇔ increase of color saturation, illuminant lighting compensation, etc.

... and others....

pointwise operations

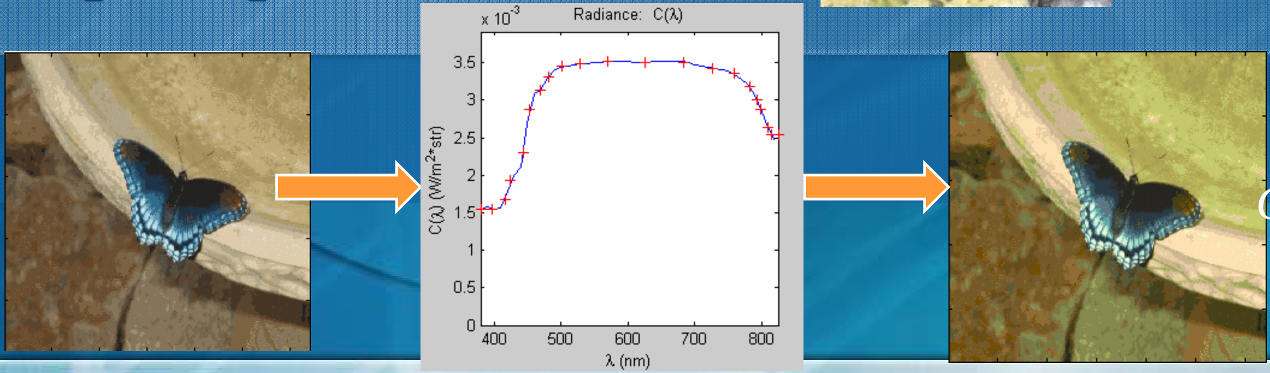
3. Image de-blurring
4. Edge enhancement

... and others...

spatial operations

contrast

saturation



Changing illuminant

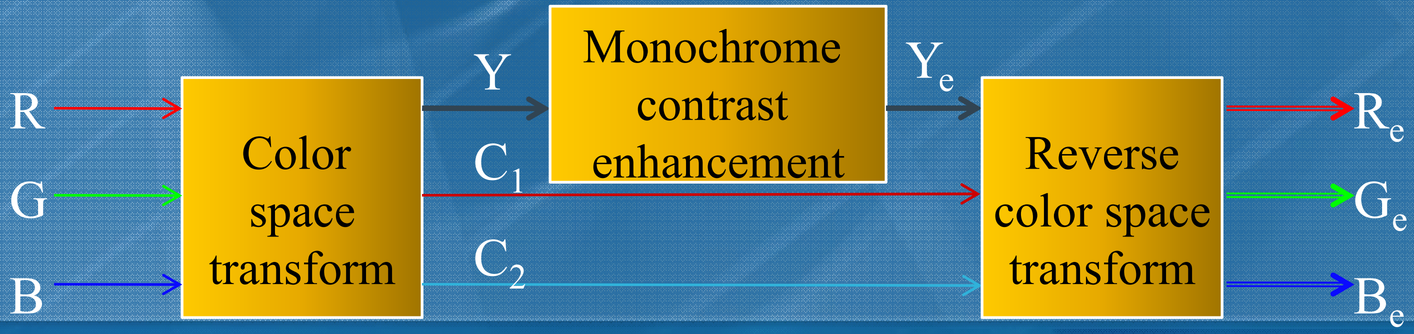
4.3. Color image enhancement (2)

- **E.g. Contrast enhancement in color images:**
  - **Basic (popular) approach:**

    ⇒ human eye - 5 more sensitive to brightness contrast then color contrast

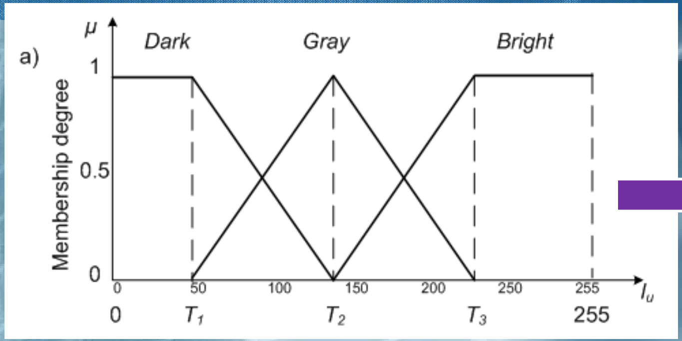
    ⇒ can achieve good contrast enhancement on brightness component alone!

    ⇒ typically:

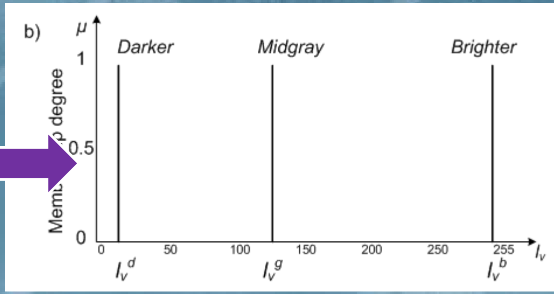


4.3. Color image enhancement (3)

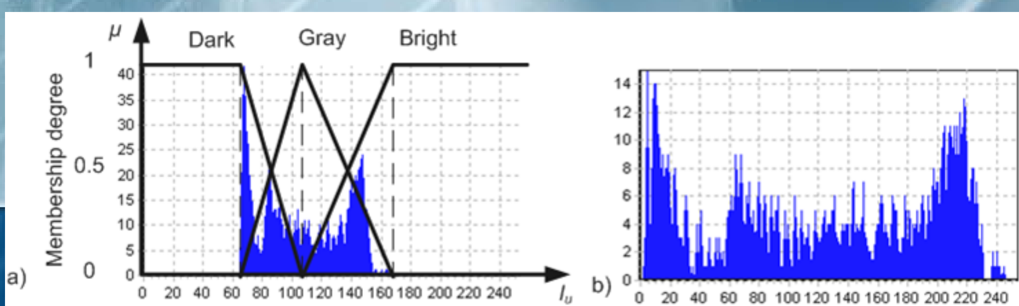
- **A simple approach: fuzzy rule-based contrast enhancement:**



Fuzzy rules:
If Y is Dark => Y_e is Darker
If Y is Gray => Y_e is Midgray
If Y is Bright => Y_e is Brighter



4.3. Color image enhancement (4)



5. Color image segmentation

- **Segmentation =** partition the image in disjoint homogeneous regions
- ***"Good segmentation"*** (Haralick & Shapiro) ⇔:
  - Uniform + homogeneous regions in respect to some visual features
  - Regions interiors – simple, without many small holes
  - Adjacent regions – significantly different visual feature values
  - Region boundaries – simple, smooth, spatially accurate

- ***Formal definition***: **I** – image set of pixels => segmentation of **I** = the partition P of N subsets R_k ; H – some homogeneity predicate =>:

$$\bigcup_{k=1}^{N} R_k = \mathbf{I}; \quad R_k \bigcap R_l = \Phi, \forall k \neq l; \quad H\left(R_k\right) = true, \forall k; \quad H\left(R_k \bigcup R_l\right) = false, \forall k \neq l \quad adjacent.$$

- **Color & texture – basic homogeneity attributes for segmentation**
- **Main color image segmentation categories:**
  1. Feature space based methods => no spatial neighborhood constraints
  2. Image domain based methods => spatial neighborhood constraints
  3. Physics based methods => special class; not found on grey scale methods

5.1. Feature space color image segmentation (1)

- **"Generalizations" of classical grey scale image segmentation strategies**
- **Two main approaches:**
    1. Color clustering
    2. Histogram thresholding

- Main issue: what color features are the most suitable for clustering/histogram analysis? => application/image content dependent!
- Segmentation strategies => still research/open issues, since ***good segmentation = "basic ingredient" for good image analysis***

- ***Current state-of-the art trends:***
    - to combine the use of low level, intermediate level and high level features;
    - to use learning => supervised segmentation (model-based)
    - describe and make "clever" use of a-priori info!

5.1. Feature space color image segmentation (2)

1. Color clustering:
= Non-supervised classification of objects/pixels ⇔ algorithms that **generate classes/partitions without any a-priori knowledge**
=>All basic methods for **any feature vectors clustering** can be applied; any color space can be used => feature space = the color space; most common:

- ***K-means:*** (iterative procedure)
K – number of clusters (user–defined); $\mathbf{S}=\{\mathbf{s}_1, \mathbf{s}_2,\ldots, \mathbf{s}_N\}$ – pixels' colors; $V=\{v_1,\ldots ,v_K\}$ – an initial random set of color prototypes; ||.|| – a distance norm in the color space
U[K N] = membership degrees matrix for the N colors in **S** to the K classes: $U=\{u_{ji}\}$, j=1,2,…,K; i=1,2,…,N:

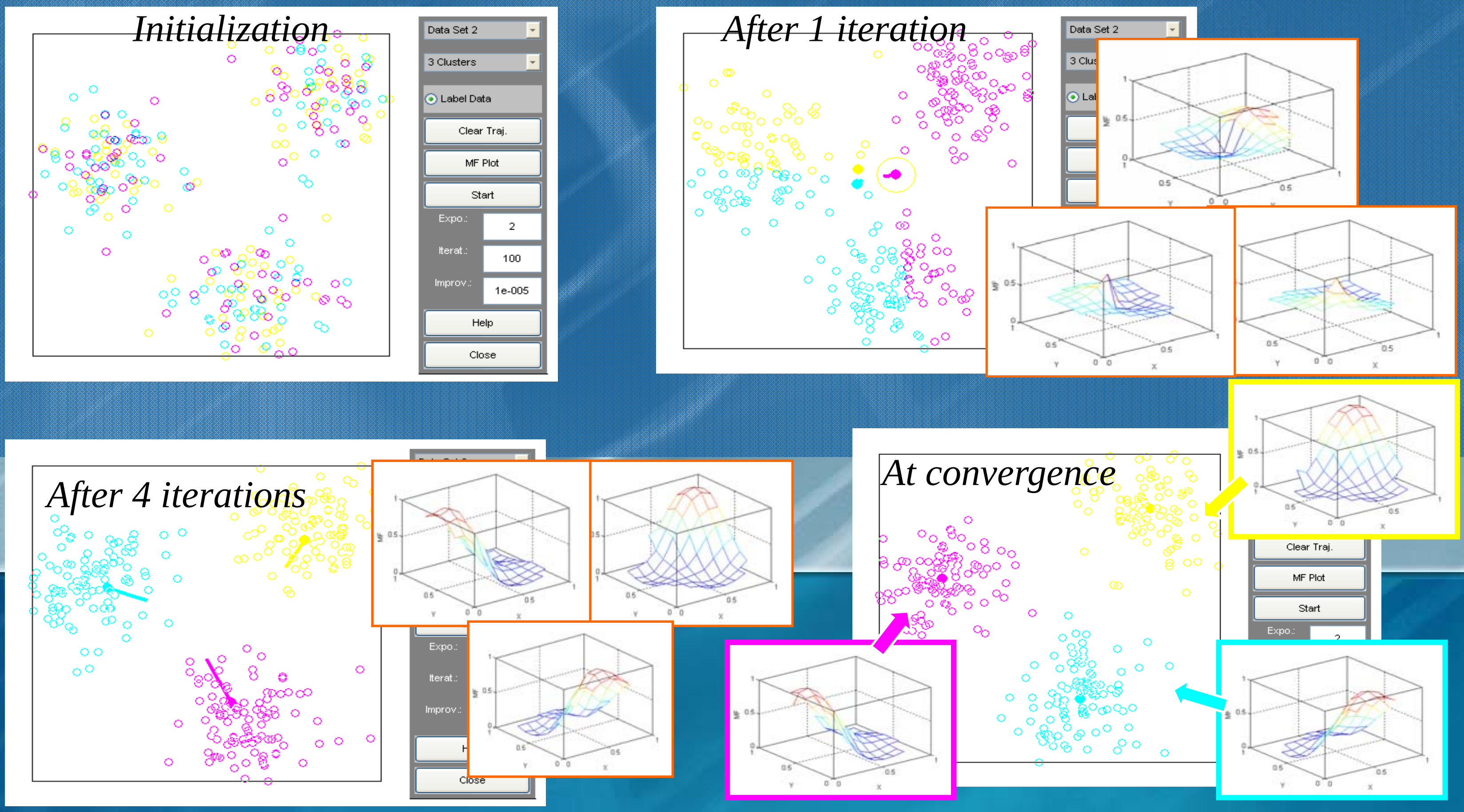
$$u_{ji} \in \{0;1\}, \quad u_{ji} = \begin{cases} 1, & \left\|\mathbf{s}_i - \mathbf{v}_j\right\|^2 = \min\limits_{k=1,2,\ldots,K} \left\|\mathbf{s}_i - \mathbf{v}_k\right\|^2 \\ 0, & otherwise \end{cases}.$$

Clustering objective: find **U**, V that minimize the cost function:

$$J(\mathbf{U},\mathbf{V}) = \sum_{j=1}^{K}\sum_{i=1}^{N} u_{ji}\left\|\mathbf{s}_i - \mathbf{v}_j\right\|^2.$$

5.1. Feature space color image segmentation (3)

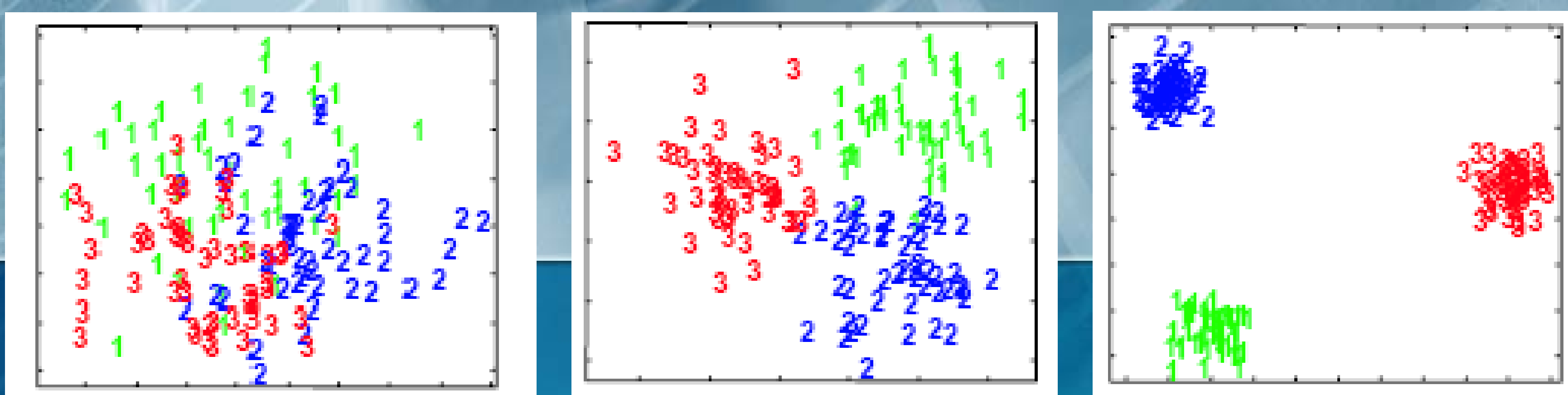
- ***Fuzzy K-means*** (⇔ fuzzy c-means): the "soft version" of K-means



5.1. Feature space color image segmentation (4)

- Many other clustering methods: ISODATA, mean shift, constrained gravitational clustering, graph partitioning, adaptive k-means, and supervised methods (***Bayesian color models, Kohonen maps, elipsoidal constrained color clusters***)

- ***Note:*** selection of the color space – application dependent; controls the success of correct clustering => quality of the segmentation!



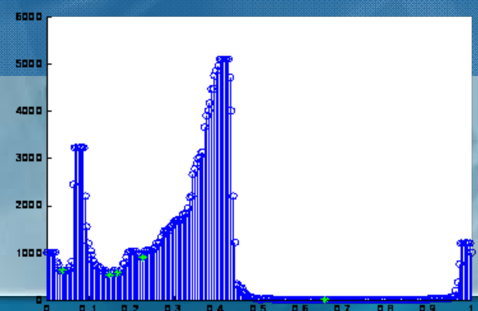
5.1. Feature space color image segmentation (5)

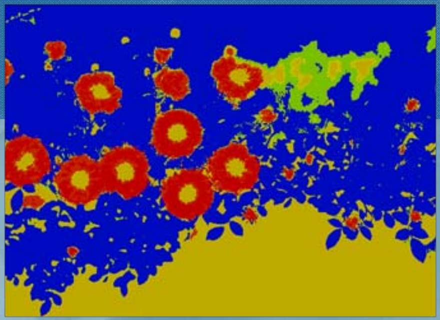
2. Histogram thresholding:

- Very popular for grey scale images: peaks & valleys detection; peaks = significant clusters; valleys = boundaries between clusters
- ***Main problem*** in generalization to color image segmentation: ***histogram = 3-D support function*** => unlike the 1-D support function for grey scales

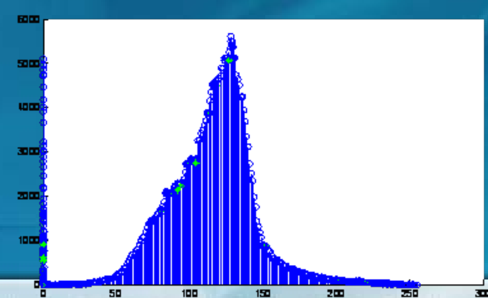
=> (1) Attempt to find the ***most relevant color feature*** to have a 1-D histogram in the color space case; commonly – use the hue H

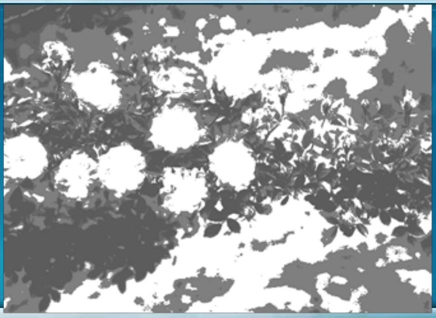
Hue





Brightness

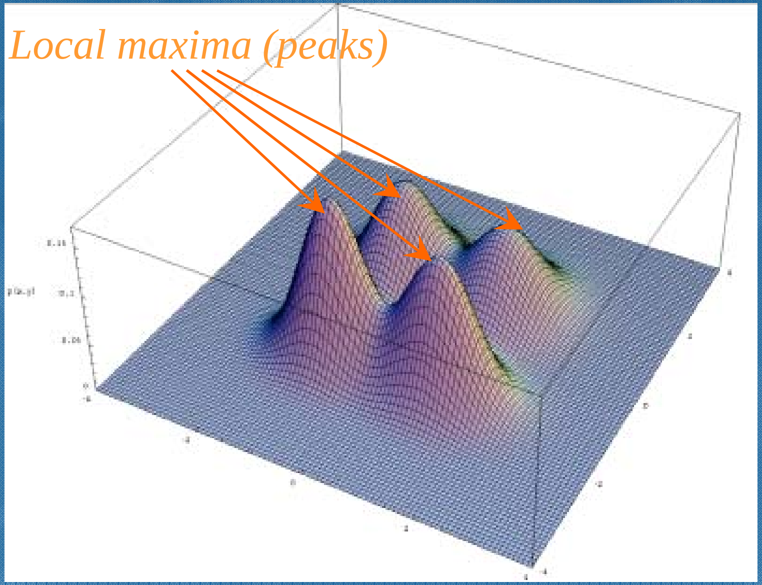




5.1. Feature space color image segmentation (6)

(2) Independently threshold the 3 color features histograms (in some color space) + use logical predicates to combine segmentation results

(3) Use pairwise features: e.g. (H,S)
=> 3-D surfaces as histograms
=> find peaks and valleys
=> segmentation



(4) Histograms modeling by Gaussian pdfs on each component in a decorrelated color space

.... Etc....

5.2. Image domain segmentation of color images

- **Previous techniques *don't guarantee spatial compactness of regions***

⇒ Image domain segmentation techniques add spatial constraints to improve segmentation (wrt compactness)

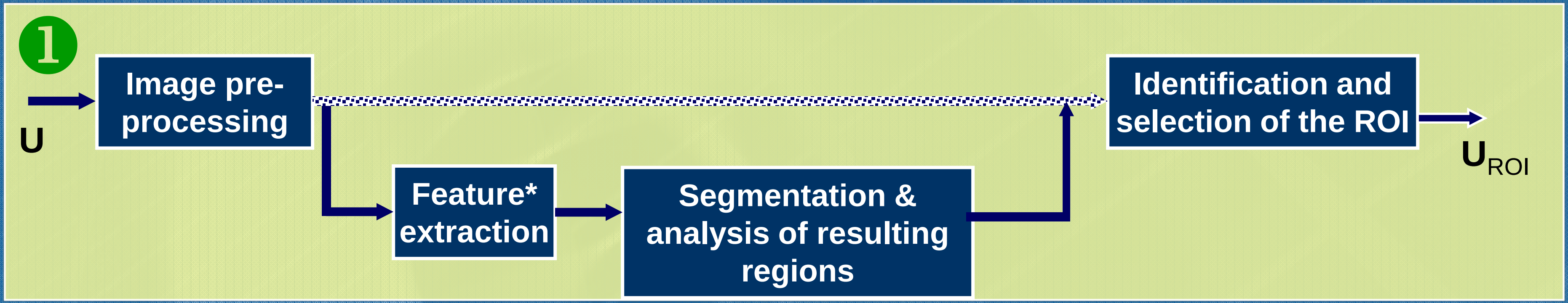
- **Two main approaches** (as in grey scale):
  1. Split – and – merge; e.g. most typical: quad-trees decomposition + merging
  2. Region growing; as in grey level case => need solutions to find good seeds

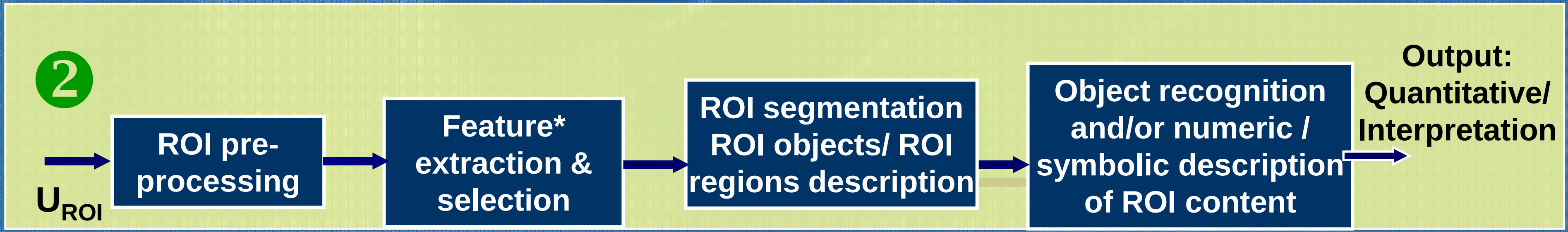
- **Main issue:** the ***similarity concept*** must be expressed in 3-D space! (distance measures ⇔ similarity measures between colors, not between grey levels) (E.g. use RGB and Euclidian distance as measure of "closeness" of colors)
- Some approaches use subsets of color features - i.e. H, S or H, V

- ***Note:*** edges can be also used; either on brightness, or the generalized 3-D gradient

6. Color image analysis

- **Analysis** – image content interpretation, far beyond processing & segmentation:





* Several studies say: ***color = the most expressive visual feature***

- ***Main challenges in color image analysis*** (esp. image retrieval, object recognition):
  (1) *develop high-level features for semantic modeling the image content;*
  (2) *fill the gap between existing (low-level, intermediate-level features) and high level features + variety of features that can be described by an observer*

6.1. Color features

- **What are they?**
  - Everything that can be extracted from color spaces
- **How can they be used?**
  - in color image indexing/retrieval: used to match objects by color similarity
  - in medical analysis, aerial imaging: used to classify color regions & to recognize specifically colored objects
  - Classical object matching applications (using color): color template matching; color histogram matching; hybrid models
  - More advanced use of color features: embed information about the ***spatial organization of colors*** (=intermediate level feature) & pixel independence relationships; => compare images with EMD (Earth Mover Distance)
- **Open issues?**
  - Usually – color features vary under various illuminant condition => suggested: define high-order invariant color features & entropy-based similarity measure
- **Standardizations:**
  - MPEG-7 color descriptors: color space; color quantization; dominant colors; scalable color; color layout; color structure; GOF/GOP color; room for more...

6.2. Color-based object tracking

- Many applications: surveillance; video analysis; robotics; videos coding; human-computer interaction; etc.

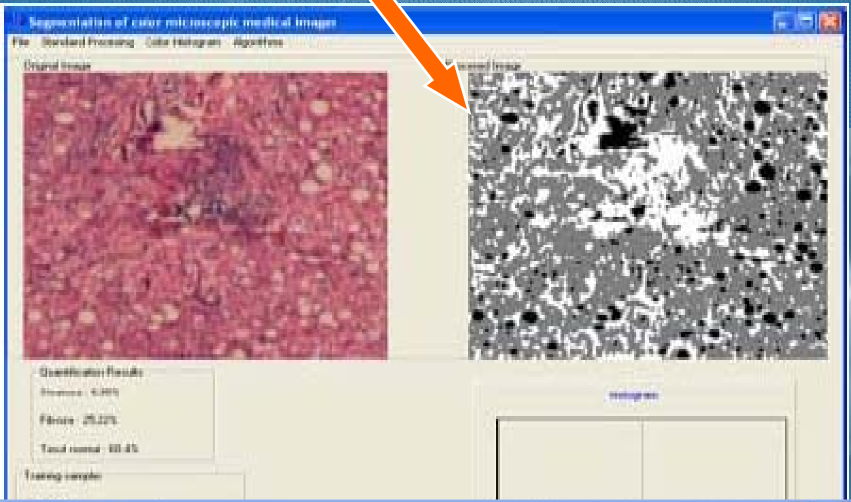
- Why is the color so useful for such applications?
  - robust in partial occlusion cases
  - robust against shape deformation & field of view changing

- **Main approaches: color models based:**
  - Semi-parametric models: mixtures of Gaussians (MoG) ; combined with EM
  - Non-parametric models: color histograms; combined with Bhattacharrya distance, mean-shift algorithm

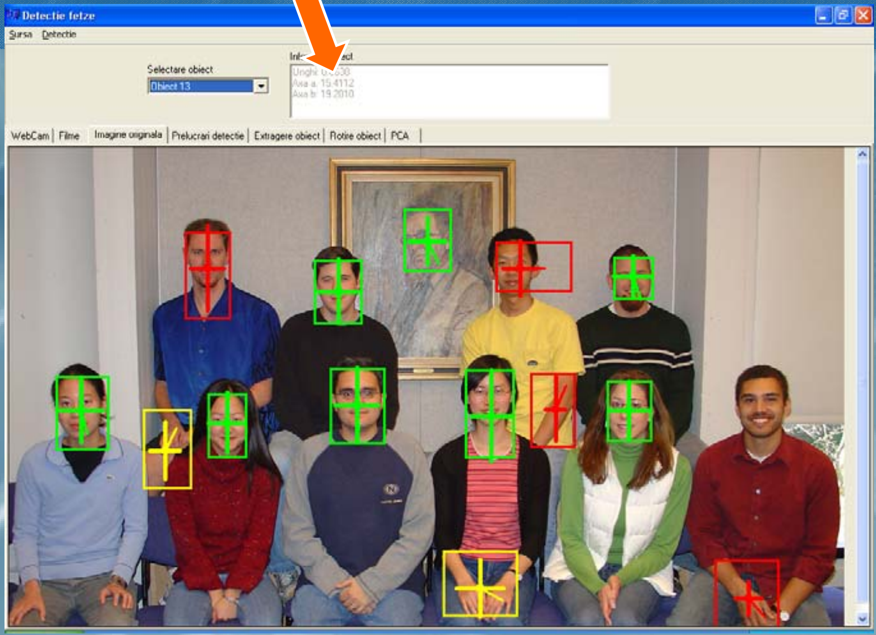
- **Other approaches:** stereo vision + color; active color appearance models

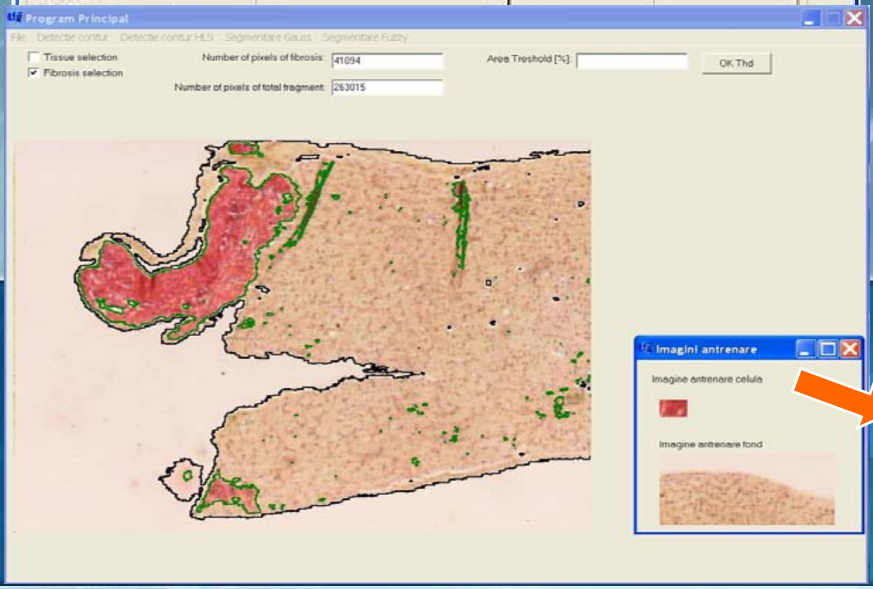
6.3. Some analysis examples

Cell counting



Face detection & localization





Liver biopsy morphometry

6.4. Some open issues: color saliency; color constancy

- **Color saliency:**
  - ***Color saliency models*** = model how HVS ***perceives*** color based on its spatial organization
  - ***Theory:*** HVS => ROI selection guided by neurological + cognitive processes
    - ***Neurological selection:*** by bottom-up (stimuli-based) info
    - ***Cognitive selection:*** by top-down (task-dependent) cues
  - ***Currently =>*** color models don't use color saliency info satisfactory (some saliency maps exist only from RGB data, not spatial info);

    => e.g. don't use HVS learned knowledge as: more attention given to color details than uniform large patches; color perception is depending on the surrounding colors

    => future research needed ***on developing perceptual multiscale saliency maps based on competition between bottom-up cues*** (color, intensity, orientation, location, motion)

6.4. Some open issues: color saliency; color constancy

- **Color constancy:**
  - In HVS: Color constancy = the subconscious ability to separate the illuminant spectral distribution from spectral surface reflectance function
    ⇔ to recognize the color appearance of an object invariant to illuminant
  - ⇒ In machines: Color constancy = ability to measure colors independent on the color of the light source (illuminant)
  - ⇒ Important goal, but ***very difficult to achieve; open research issue***

  - Some approaches:
    - Illuminant estimation algorithms: max-RGB, gray-world, gammut mapping, Bayesian models, neural networks;
    - Use high-level visual information for illuminant estimation: model objects by semantic info (i.e. green grass, blue sky) + add color knowledge
    - Use physics scenarios => but don't always match the real illuminant source mixture...