

# So far...

- Considered processing of **greyscale** images
- $I[m,n]$  is a function defined over a 2-D discrete space

$$I: \mathbb{Z}^2 \rightarrow \mathbb{Z}$$

I.e. greyscale image is a **scalar valued** function

What if the image is a **vector valued** function?

$$I: \mathbb{Z}^2 \rightarrow \mathbb{Z}^n$$

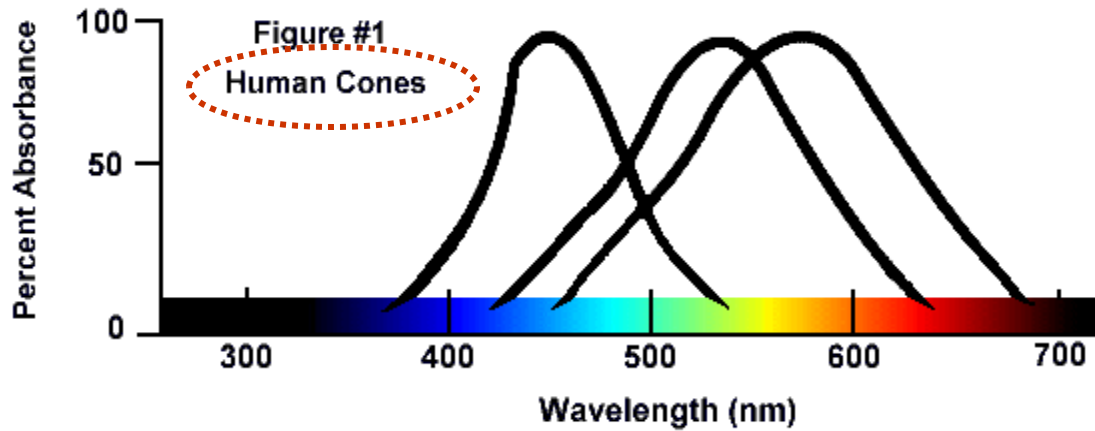
Ex. Colour images ..... Different  $n$  for different sensors

# Colour models

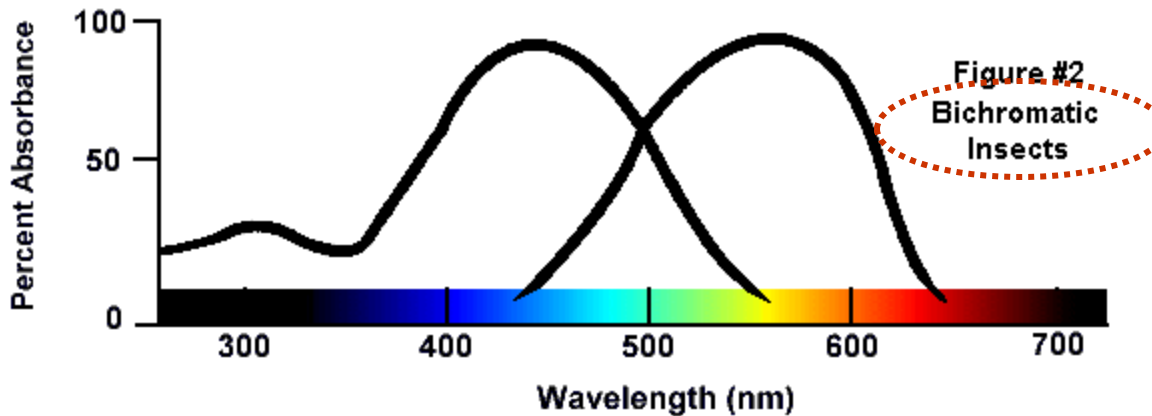
# Colour basics

- Light  $\equiv$  electromagnetic wave (photons)
  - velocity : c
  - frequency : f
  - wavelength :  $\lambda$
- $$\lambda f = c$$
- **Colour** - response of a sensor to photons of different wavelength
  - **Spectral sensitivity** of a sensor determines the range of colours it can “see”

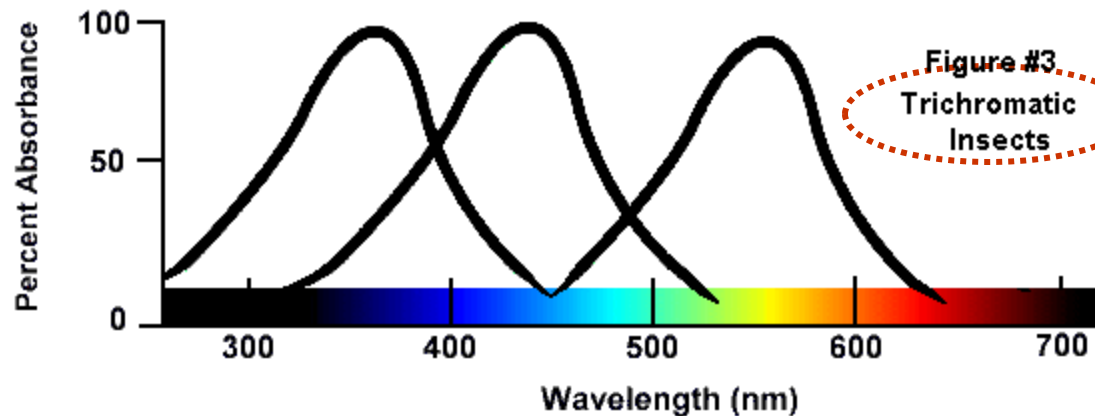
# The visible world of different creatures



Humans are  
uv-blind

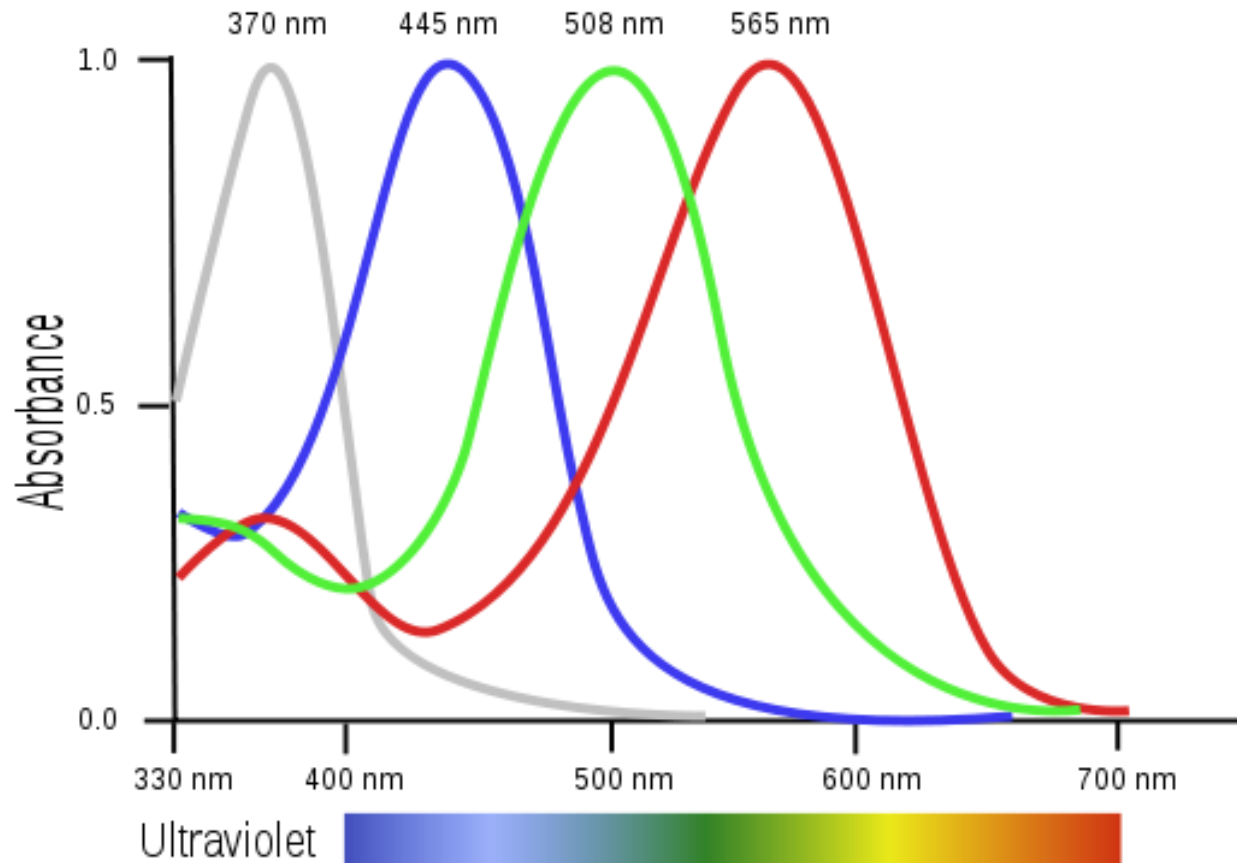


Many insects  
don't see  
red well!  
 $n=2$



honeybees,  
bumblebees and  
butterflies have  
widest and *true-*  
*colour* vision  
 $n=3$

# Birds - Tetrachromatic vision



Pigeons have pentachromatic vision

# The balsam flower as seen by



humans



bees



butterfly

The world we perceive is different!

<http://landsat.gsfc.nasa.gov/education/compositor/em.html>

# Visual world of machines

Wide-spectrum imaging is possible by using different types of *special sensors*

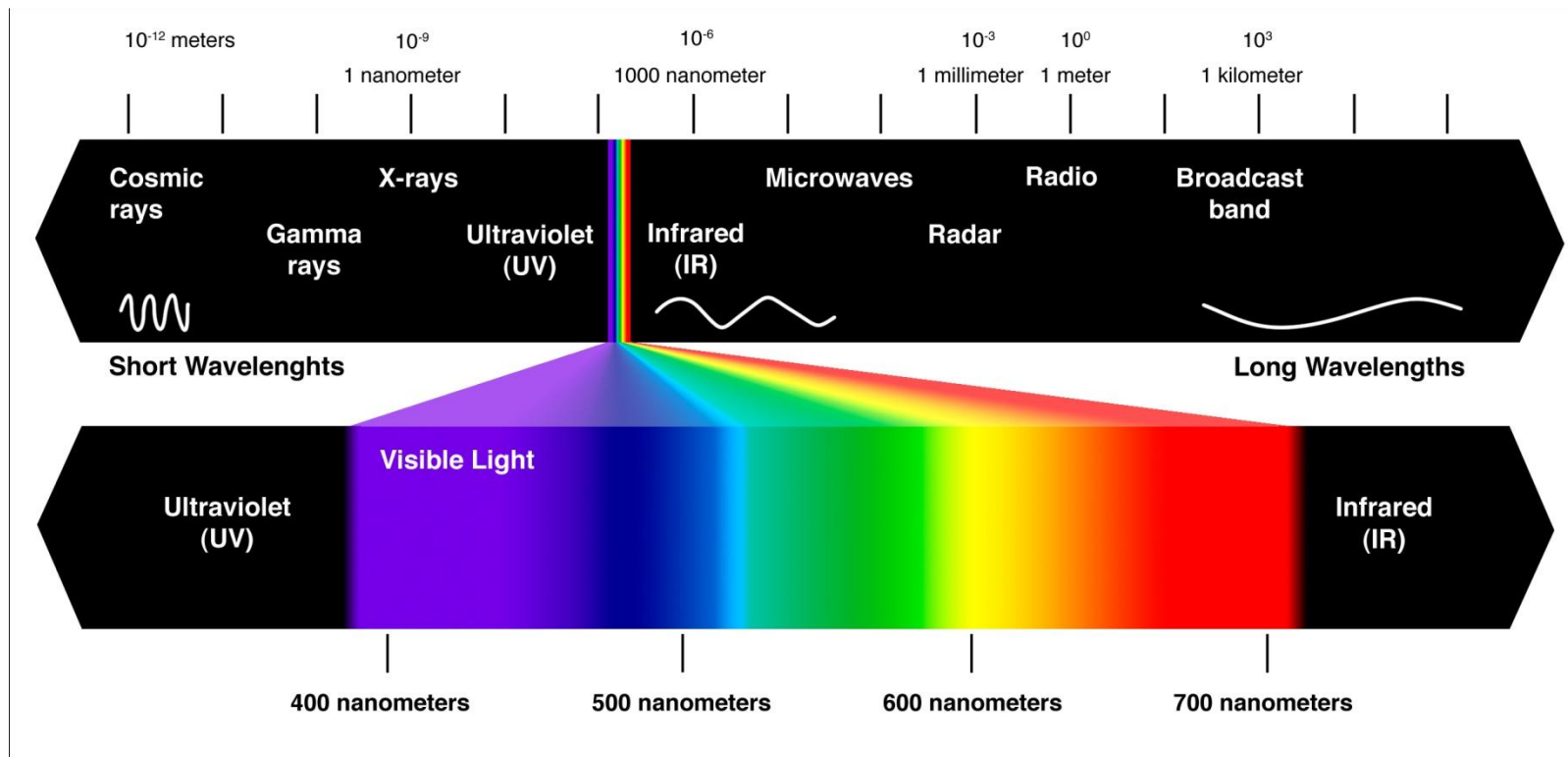
Ultraviolet range: 100 - 380 nm

Visible range: 380 - 780 nm

Mid-infrared: 1400 - 3300 nm

Near-infra red: 780-1400 nm

Far-infrared: 3 -10  $\mu\text{m}$



# Representing colour

- Spectral colour space (continuous)
- By sampling this space (using sensors) we get the sampled space  $c \rightarrow (c_1, c_2, \dots, c_n)$ , where  $c_i = c(\lambda_i)$  the spectral colour distribution
- A colour image  $I(x, y) = \{ c_i(x, y) \}$
- I.e.  $I$  is a vector-valued function  $\vec{I}(\vec{r}); \vec{r} = [x, y]$
- A colour space can be represented using different colour models/spaces
  - color space is usually 3-dimensional or  $i = 1, 2, 3$



# Colour models

- RGB (red, green, blue)
  - Used in image acquisition and display
- CMYK (cyan, magenta, yellow and black)
  - Used in printing
- HSI (hue, saturation and intensity)
  - Used in image manipulation
- YIQ / NTSC
  - Used in TV broadcasting
- $YC_bC_r$ 
  - Used in digital video

# RGB model

- Additive colour model

$$c(x,y) = \alpha_1 R + \alpha_2 G + \alpha_3 B$$

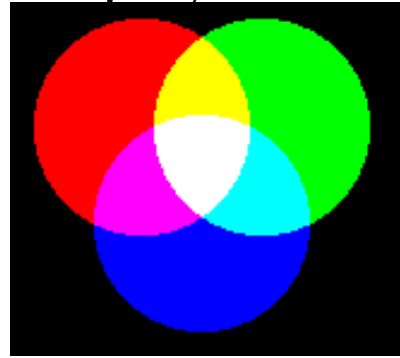
- Primary colours
  - Red (700 nm)
  - Green (546 nm)
  - Blue (435 nm)
- Non-uniform space in the perceptual sense

# CMY model

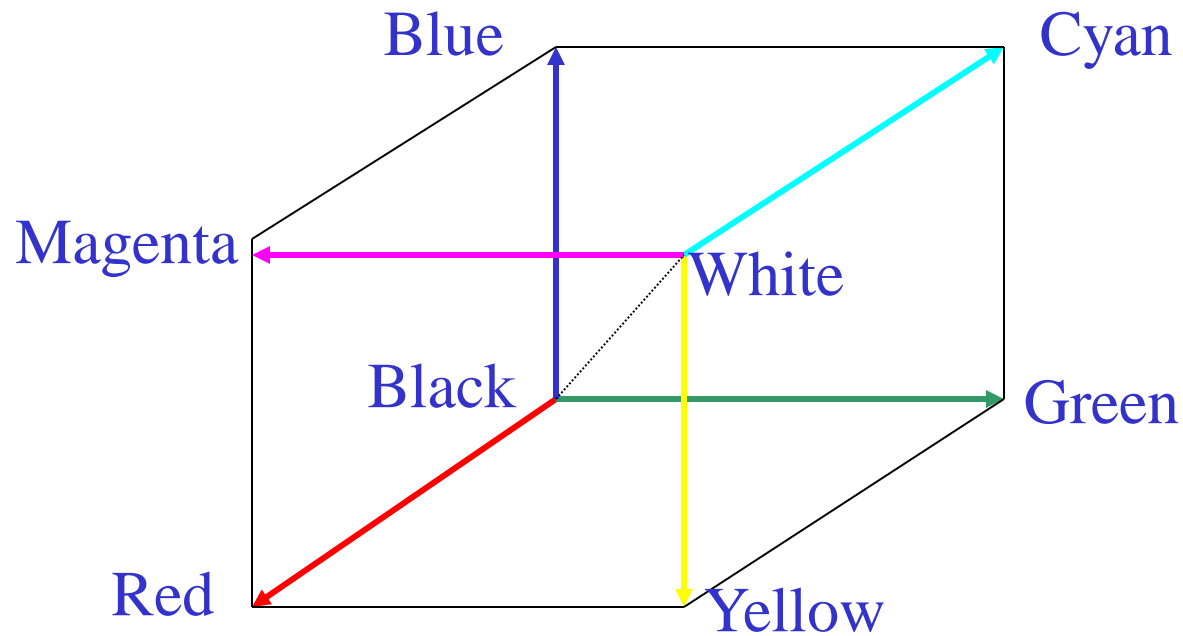
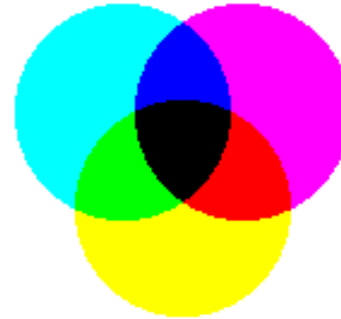
- Subtractive colour model
- Secondary colours
  - Cyan, Magenta and Yellow
  - Plus Black (to get pure black in printing)
- Non-uniform space

$$\begin{bmatrix} C \\ M \\ Y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

Display



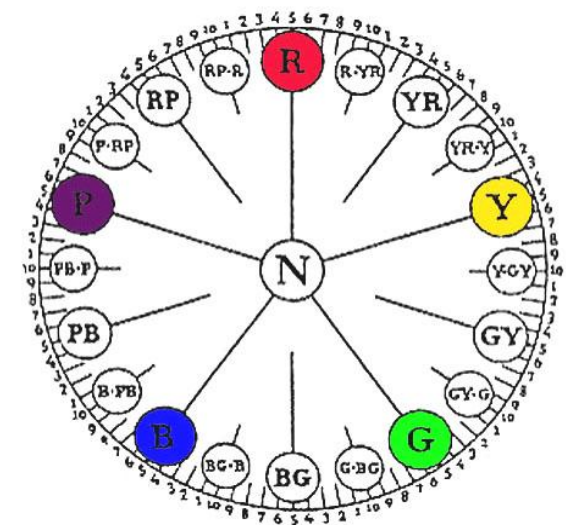
Printer



Colour cube

# HSI Model

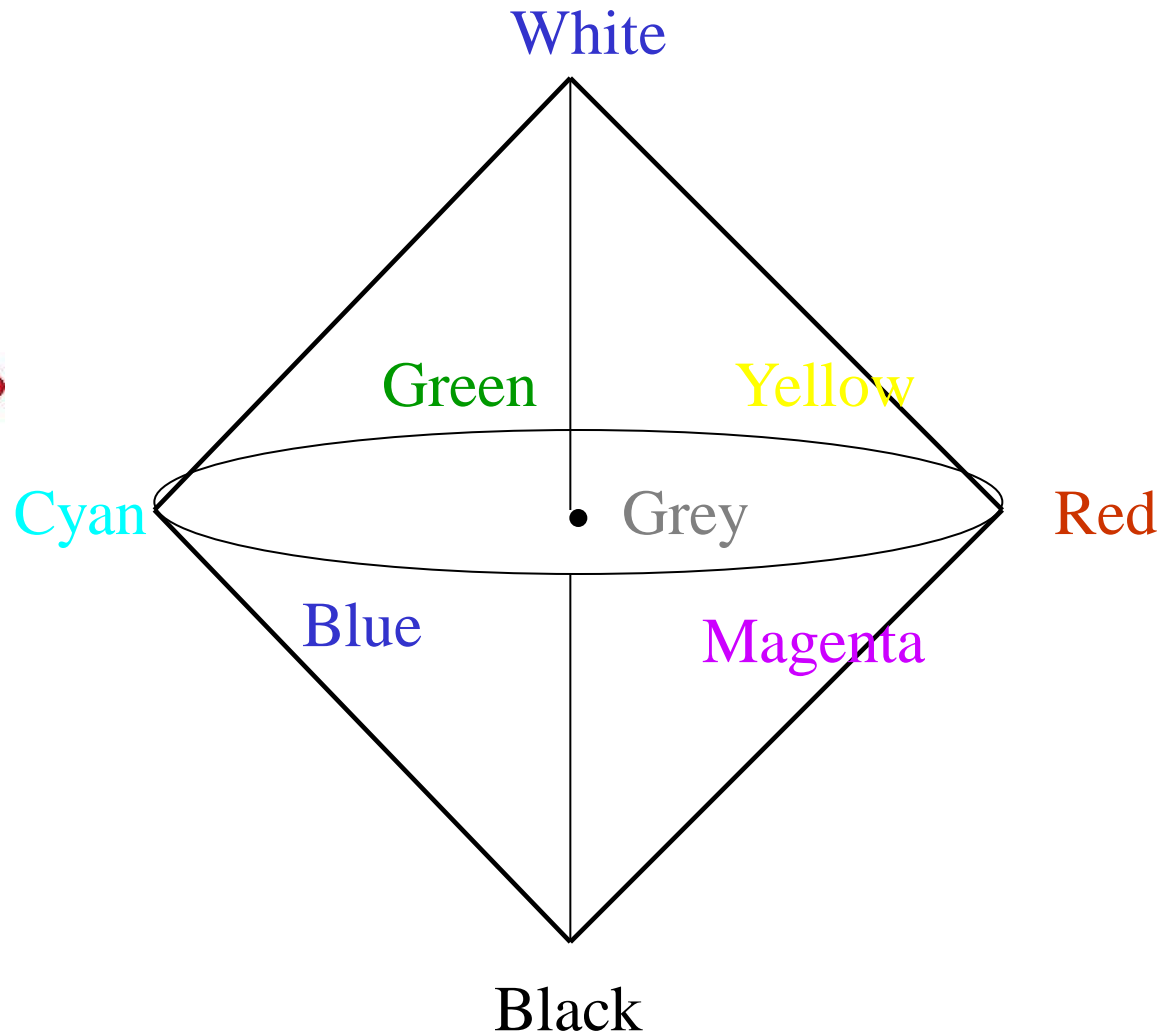
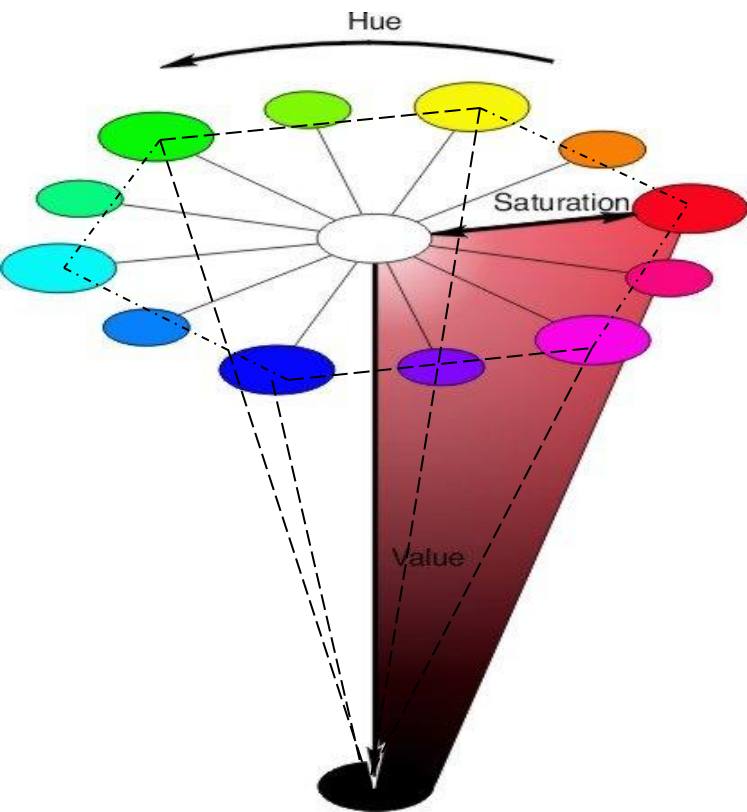
- Hue saturation and Intensity model
  - A close relative is **HSV** (for value)
- Perceptually uniform (meaningful) model
- Chromatic
  - **Hue** (400 – 700 nm)
    - Commonly understood as colour, ex: blue vs. green
  - **Saturation**
    - Spectral purity of colour ex: light blue vs. (
  - **Achromatic**
    - Intensity or grey Value



# Why HSI model?

- Decouples chromatic from achromatic info.
- Decouples spectral purity from spectral info.
  - Ex: extract red /blue regions from an image
  - Ex: brightness control without colour shift

# HSI model – Colour spindle



# YIQ (YUV) model

- Used for commercial broadcast
- **Y**: luminance (intensity or grey value)
  - More bandwidth is allocated for this
- **I** and **Q**: chromatic components
  - I is roughly (red - cyan)
  - Q is (magenta - green)
  - Less bandwidth allocated for these



# Colour synthesis

**Problem:** Given a colour spectrum  $S(\lambda)$ , create it with tri-stimulus components  $c_i(\lambda)$ ;  $i=1,2,3$

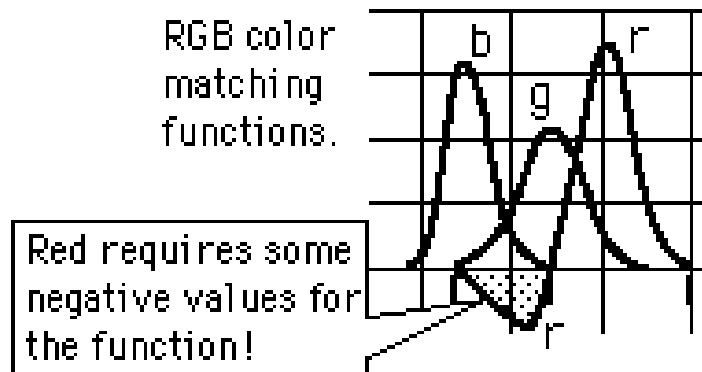
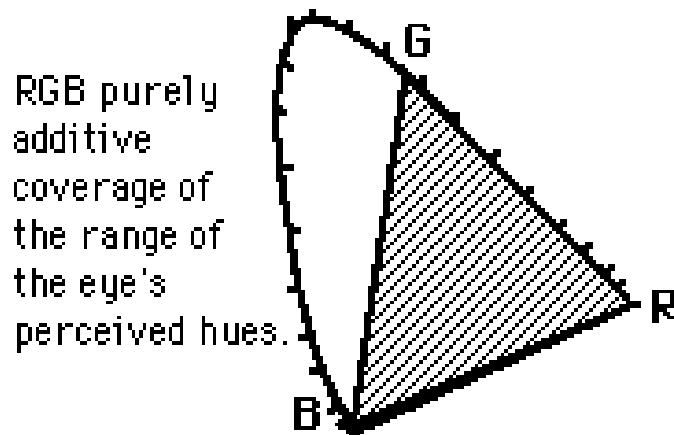
- Let us try using additive colours RGB
  - $S(\lambda)$  needs to be expressed as a linear combination of  $r(\lambda)$ ,  $g(\lambda)$ ,  $b(\lambda)$

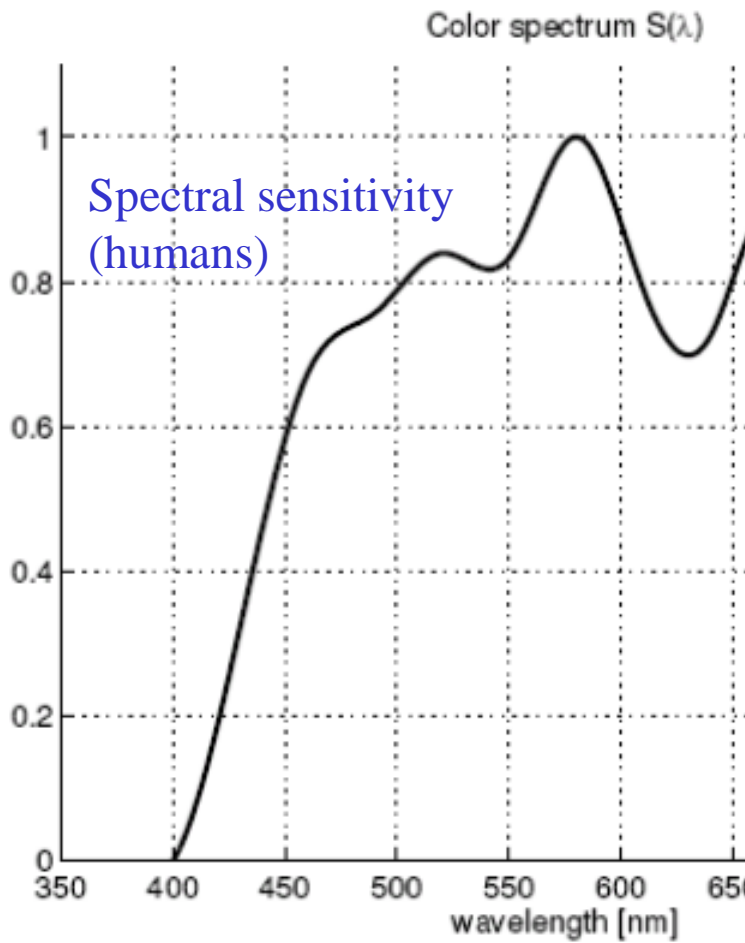
$$S(\lambda) = R \int \underset{\uparrow}{r(\lambda')} S(\lambda') d\lambda' + G \int \underset{\uparrow}{g(\lambda')} S(\lambda') d\lambda' + B \int \underset{\uparrow}{b(\lambda')} S(\lambda') d\lambda'$$

Spectral characteristics of the  $r$ ,  $g$ ,  $b$  sensors

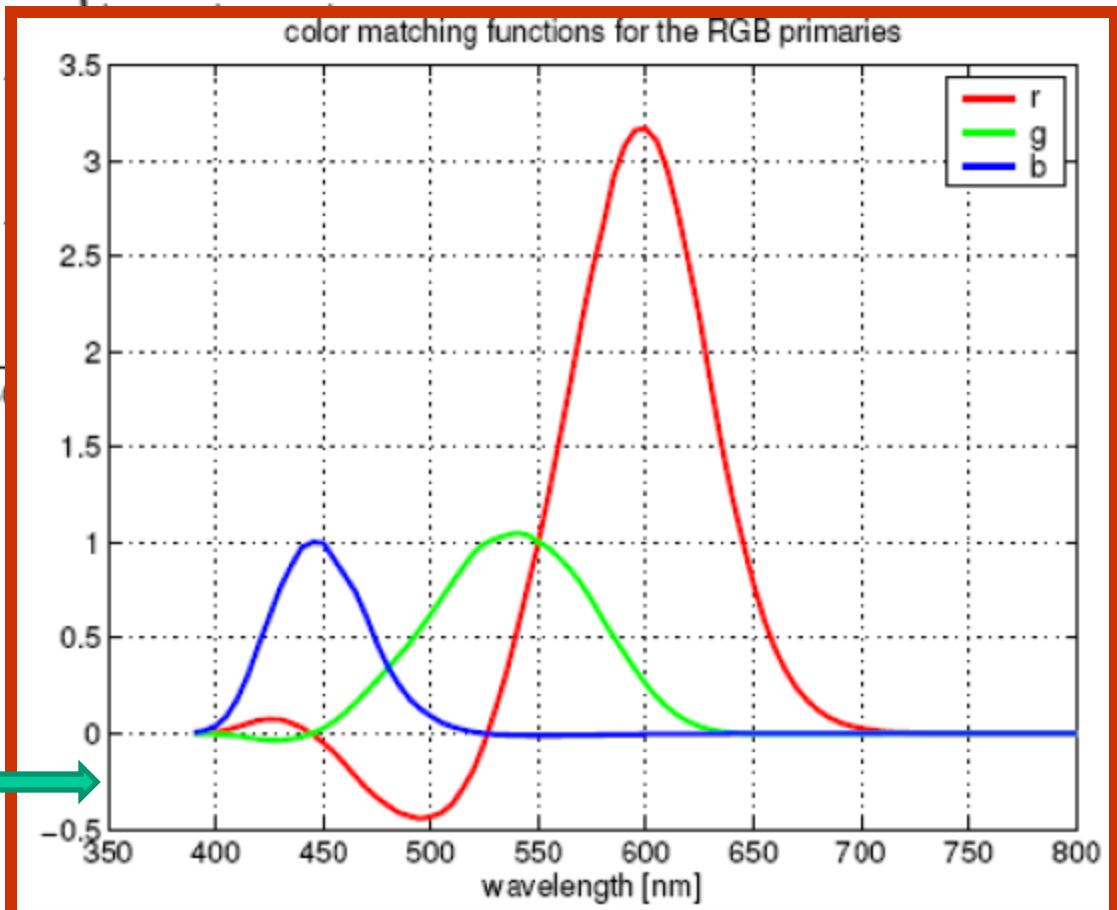
# Key fact from a 1920 experiment

- The gamut of colours that can be created by mixing RGB (primary) is **incomplete**
  - We can perceive more colours
- Need an alternate colour model



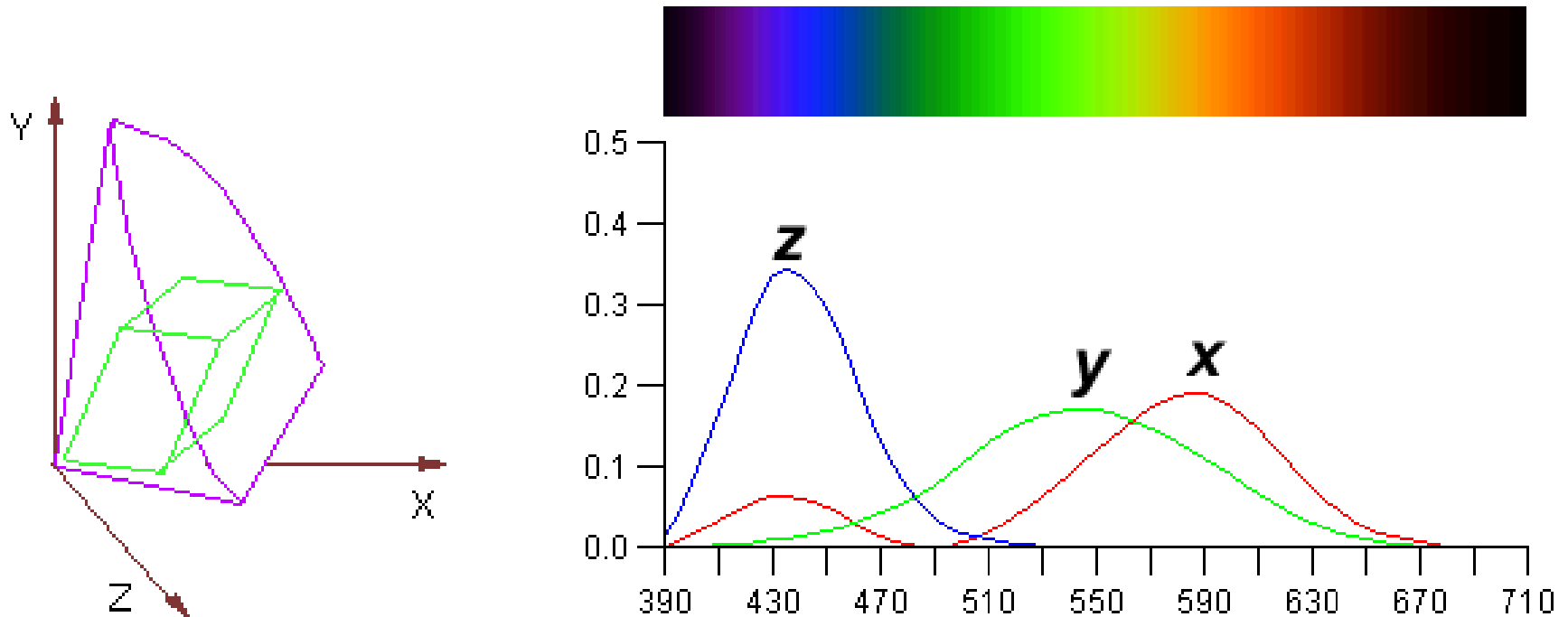


Negative values  
are needed to cover all  
perceivable  $\lambda$ !



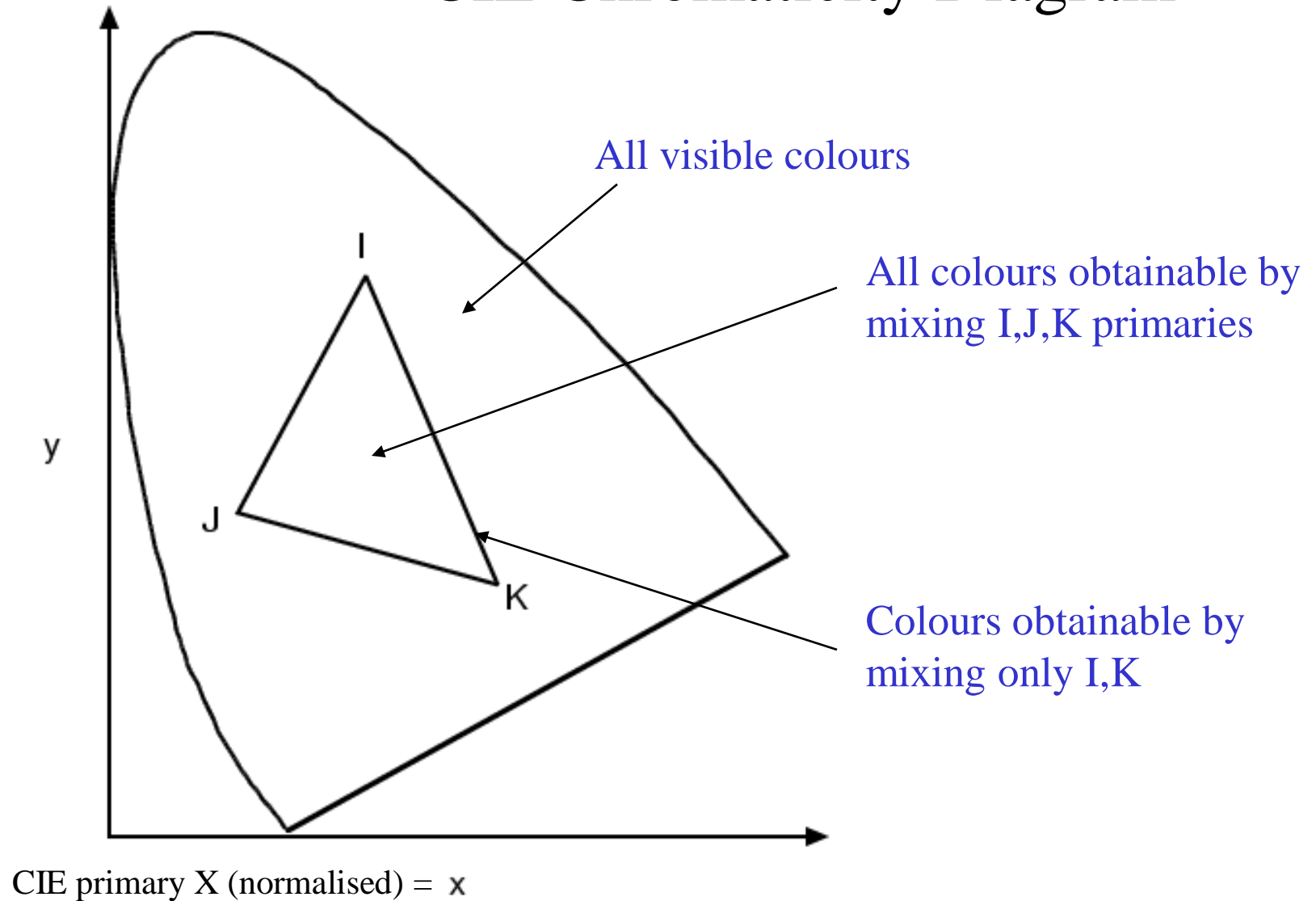
# A solution to colour mixing

CIE colour space – using hypothetical primaries



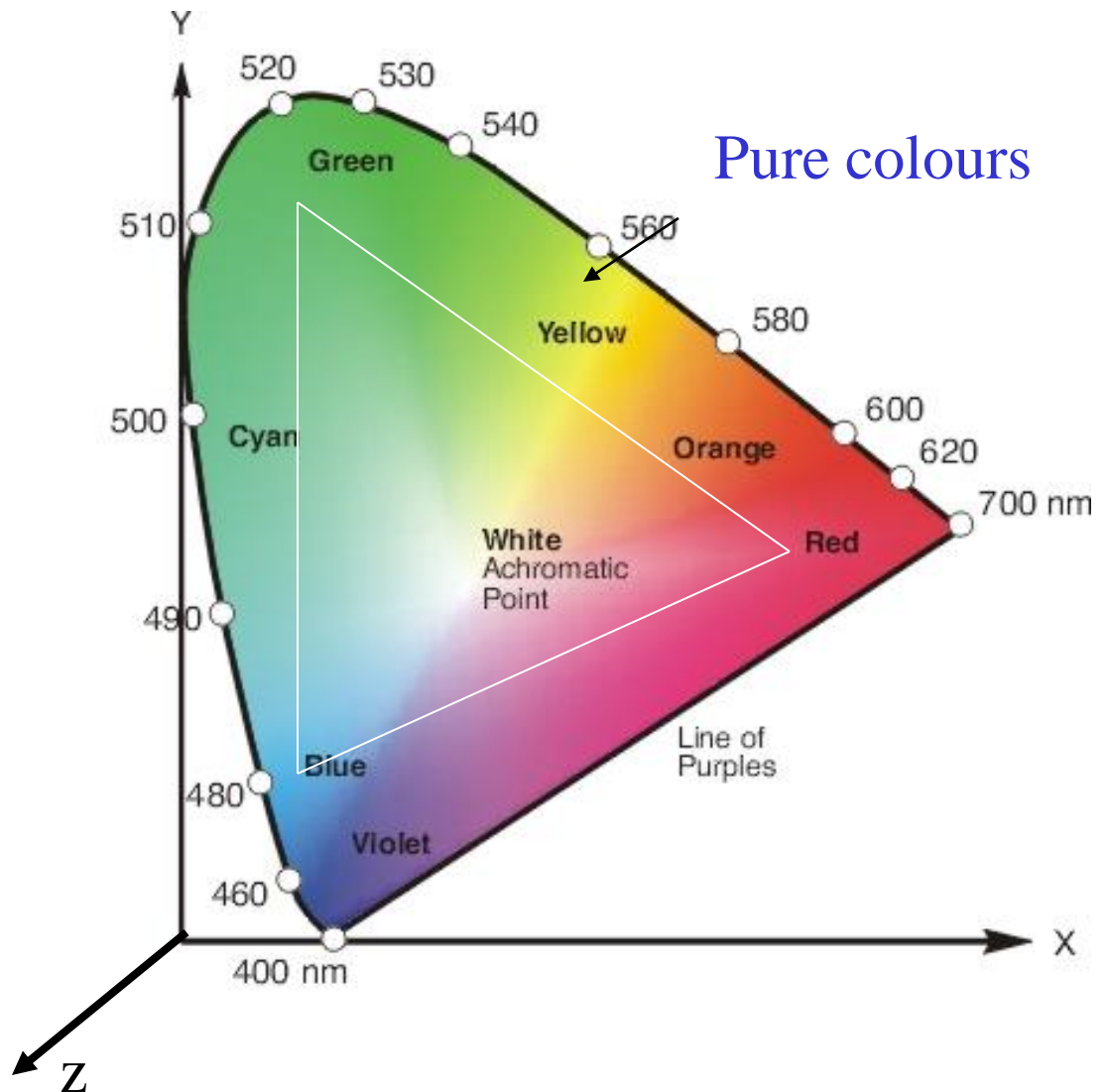
X,Y,Z are tristimulus values

# CIE Chromaticity Diagram



# CIE chromaticity diagram

- Chromaticity in a 2-D space  $(x, y) = \frac{1}{X+Y+Z}(X, Y)$
- Gamut of human eye: the parabolic region
- Gamut of a RGB display or CMY printer: a triangular region
- Used for colour measurement



# Other derivative models of CIE

*Lab* colour space

*L*:Lightness *a*:red-green *b*:yellow-blue

Colour opponent dimensions

**Advantage:** colour changes perceptually linearly as one moves across the chart

- Useful in image manipulation to achieve uniform colour shift



Colour image



Blue plane



Green plane

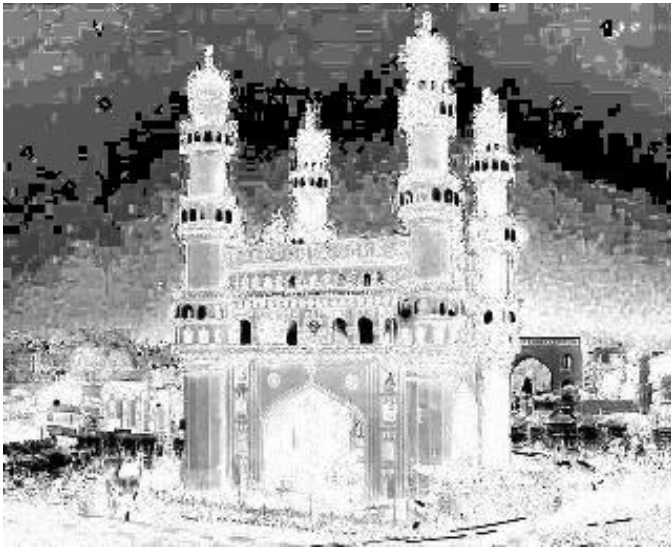


Red plane





H plane



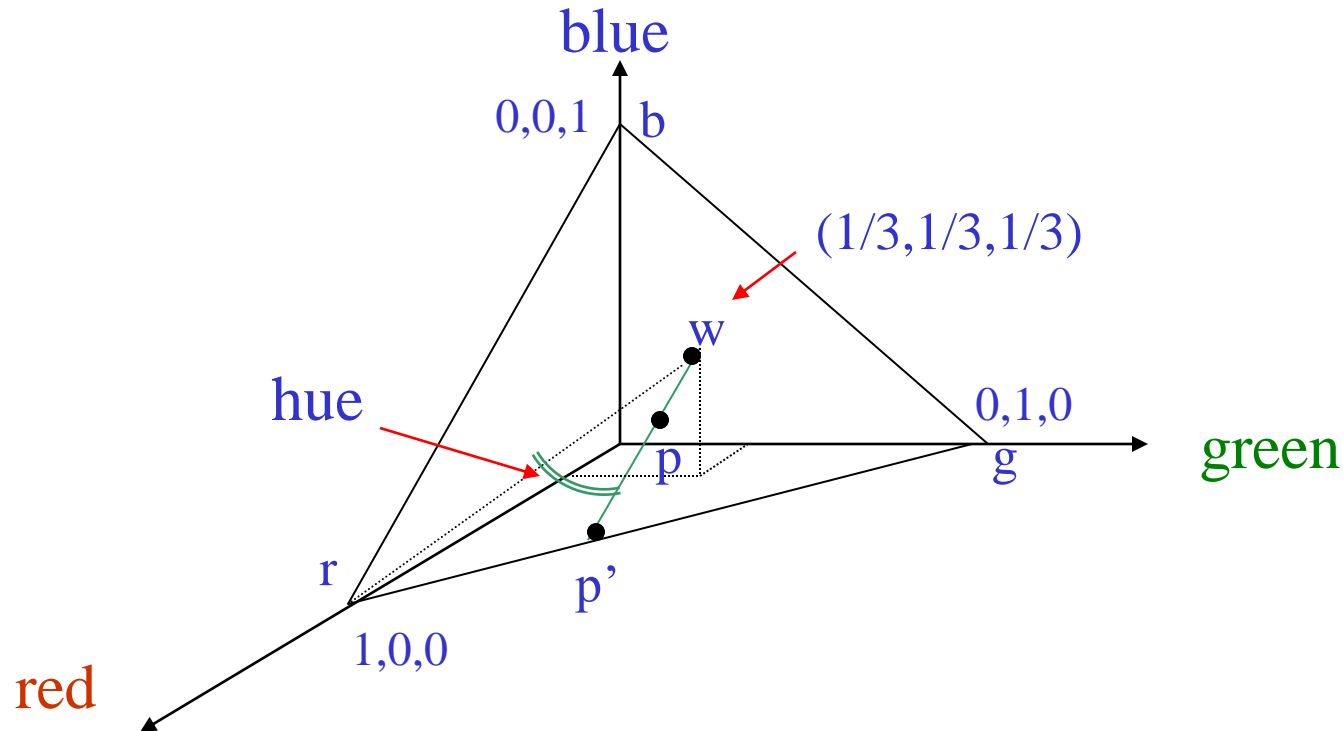
S plane



I plane

# **Conversion between models**

# RGB-HSI conversion



The angle between  $w_{p'}$  and  $w_r$  (in terms of  $r, b, c$ ) = hue

The ratio of vector lengths  $w_p$  to  $w_{p'}$  = saturation

# RGB to HSI conversion

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

$$S = 1 - \frac{\min(R, G, B)}{I}$$

$$H = \cos^{-1} \left\{ \frac{0.5[(R - G) + (R - B)]}{\sqrt{[(R - G)^2 + (R - B)(G - B)]}} \right\}$$

$\in (0, 360]$

- All variables are in  $[0, 1]$ ;  $H = H/360$  for normalisation
- $H = 360 - H$  if  $B/I > G/I$

# HSI to RGB conversion

- Similar results are derivable using the chromaticity triangle

$$r = \frac{1}{3} \left[ 1 + \frac{S \cos H}{\cos(60 - H)} \right]$$

$$b = \frac{1}{3} (1 - S)$$

$$g = 1 - (r + b)$$

# RGB-YIQ conversion

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

- For greyscale image,  $R=G=B \rightarrow I = Q = 0$
- Inverse conversion is possible using inverted matrix

# YC<sub>b</sub>C<sub>r</sub> model

- Used in digital video
- **Y**: luminance
- **C<sub>b</sub>,C<sub>r</sub>** : colour (difference) information

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

# Colour images - storage

$$\mathbf{c}[m,n] = \{c_i[m,n]; i = 1,2,3\}$$

$c_i$  is a greyscale image



Storage requirements is tripled!

- Can be reduced using **colour palettes**
  - commonly done in monitors



# Colour Palettes- indexed colour

- **True** colour image needs 3 bytes/pixel to store the image
- With 3 bytes the possible colours is  $(2^8)^3 = 16,777,216 \sim 17$  million

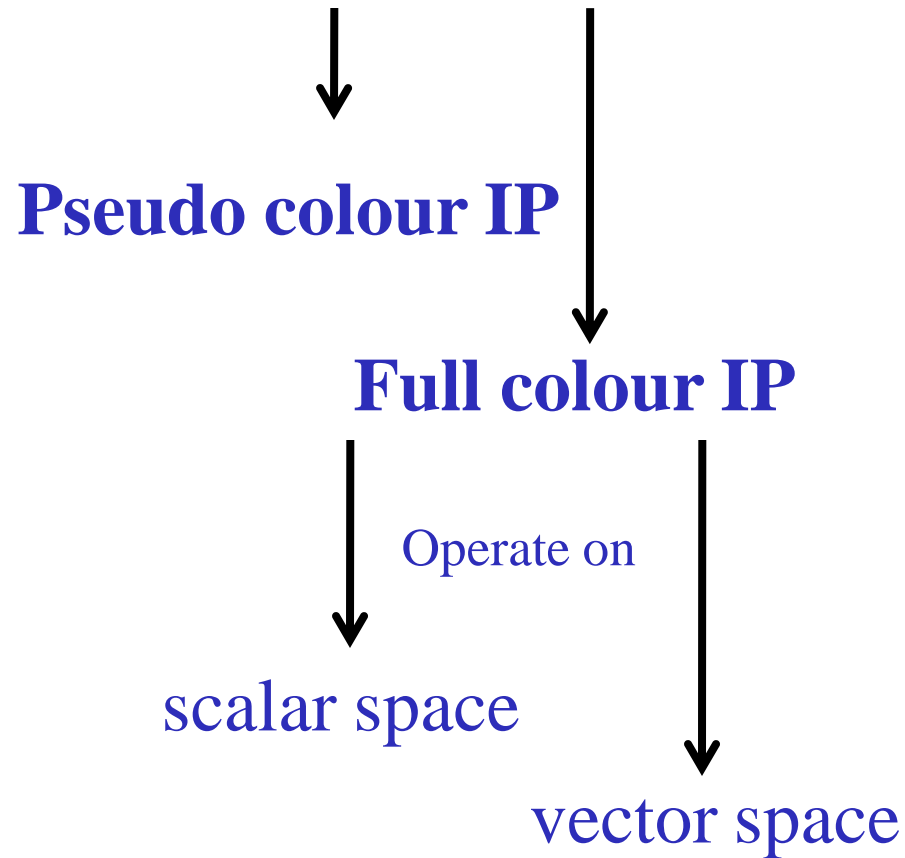
For  $M \times N = MN$  pixel image we need **3 MN bytes**

## Palette idea:

- assign 8 bits/pixel and design a limited size table of colours (palette) ex.  $2^8 \times 3$  palette  $\rightarrow$  256 colours
  - 768 bytes for palette storage
- palette is chosen from 17 million colours using some algorithm
- 1byte is for a pointer to an entry in the palette
- To store the image we now need **(MN +768) bytes**
  - (1byte/pixel x MN pixels +768 bytes)

One can assign less than 8 bits/pixel  $\rightarrow$  greater savings in storage  
At the cost of colour accuracy!

# Colour Image Processing



# calvin and hobbes

by WATTERSON

WOW, HONEY, YOU'RE MISSING A BEAUTIFUL SUNSET OUT HERE!



I'LL COUNT TO 10, AND THEN...  
**PON!**



DAD, HOW COME OLD PHOTOGRAPHS ARE ALWAYS BLACK AND WHITE? DIDN'T THEY HAVE COLOR FILM BACK THEN?



SURE THEY DID. IN FACT, THOSE OLD PHOTOGRAPHS **ARE** IN COLOR. IT'S JUST THE **WORLD** WAS BLACK AND WHITE THEN.



REALLY?

YEP. THE WORLD DIDN'T TURN COLOR UNTIL SOMETIME IN THE 1930s, AND IT WAS PRETTY GRAINY COLOR FOR A WHILE, TOO.



THAT'S REALLY WEIRD.

WELL, TRUTH IS STRANGER THAN FICTION.



BUT THEN WHY ARE OLD **PAINTINGS** IN COLOR? IF THE WORLD WAS BLACK AND WHITE, WOULDN'T ARTISTS HAVE PAINTED IT THAT WAY?

NOT NECESSARILY. A LOT OF GREAT ARTISTS WERE INSANE.



BUT...BUT HOW COULD THEY HAVE PAINTED IN COLOR ANYWAY? WOULDN'T THEIR PAINTS HAVE BEEN SHADES OF GRAY BACK THEN?

OF COURSE, BUT THEY TURNED COLORS LIKE EVERYTHING ELSE DID IN THE '30s.



SO WHY DIDN'T OLD BLACK AND WHITE PHOTOS TURN COLOR TOO?

BECAUSE THEY WERE COLOR PICTURES OF BLACK AND WHITE, REMEMBER?



THE WORLD IS A COMPLICATED PLACE, HOBBS.

WHenever it seems that way, I take a nap in a tree and wait for dinner.

# Processing colour images

- Pseudo colour IP (greyscale image input)
  - Artificially converting grey scale to colour
- Full colour IP (colour image input)
  - n-bit colour;  $n = 24, 26$
  - $n/3$  bits per component
  - pixel value is in  $[0, 2^{n/3}-1]$  or  $(0, 360^\circ]$  or  $[0, 1]$

# Pseudo colour IP

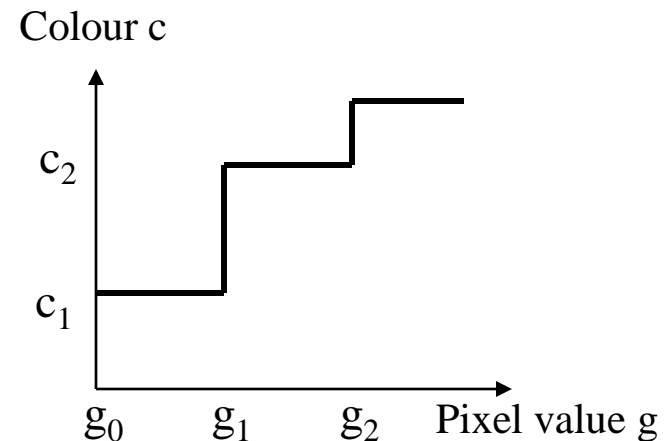
Greyscale image  $\rightarrow$  colour image

➤ to highlight some feature of interest in the image

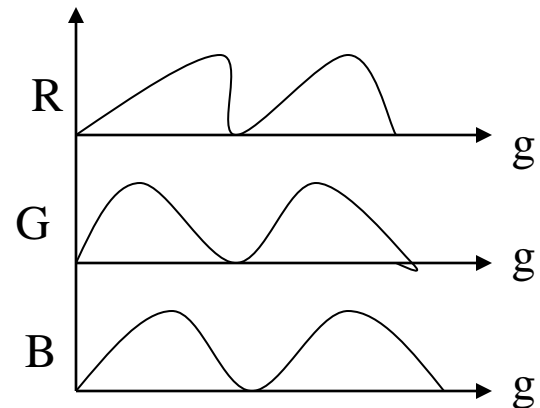
## Techniques:

- Intensity slicing

$$\begin{aligned} f(g) &= c_1 ; & g_0 < g < g_1 \\ &= c_2 ; & g_1 < g < g_2 \dots \end{aligned}$$

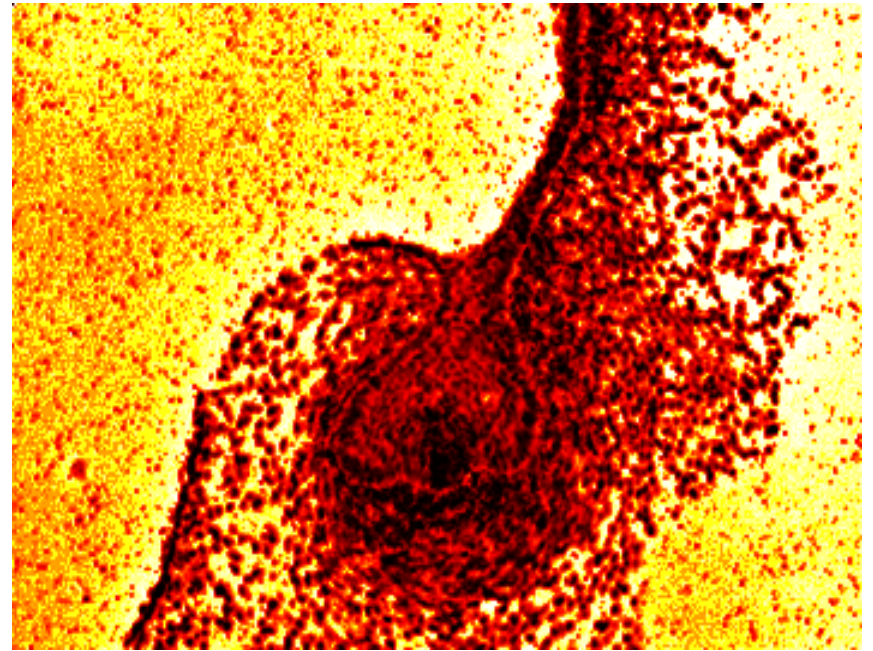
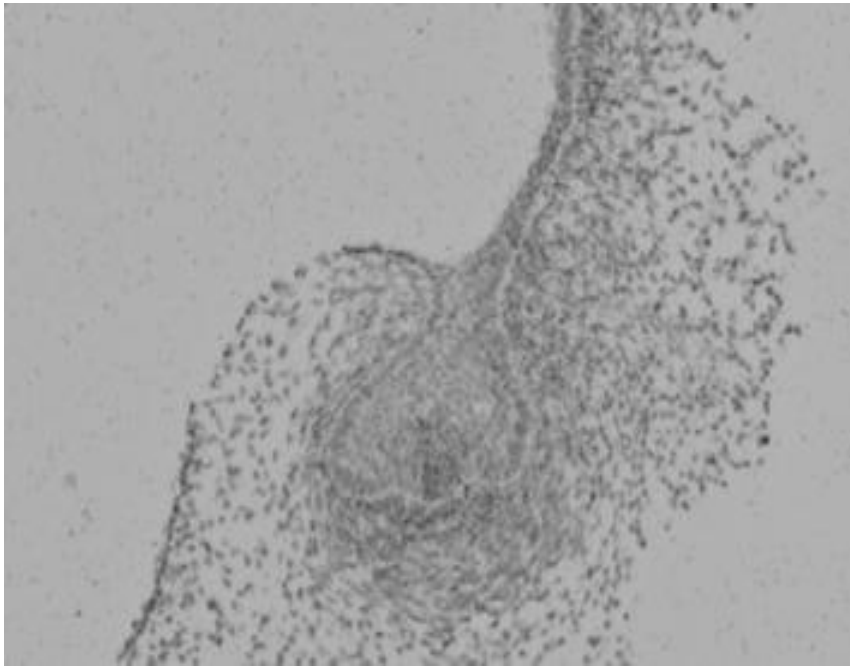


- Grey-colour transformation
  - User-defined mapping functions



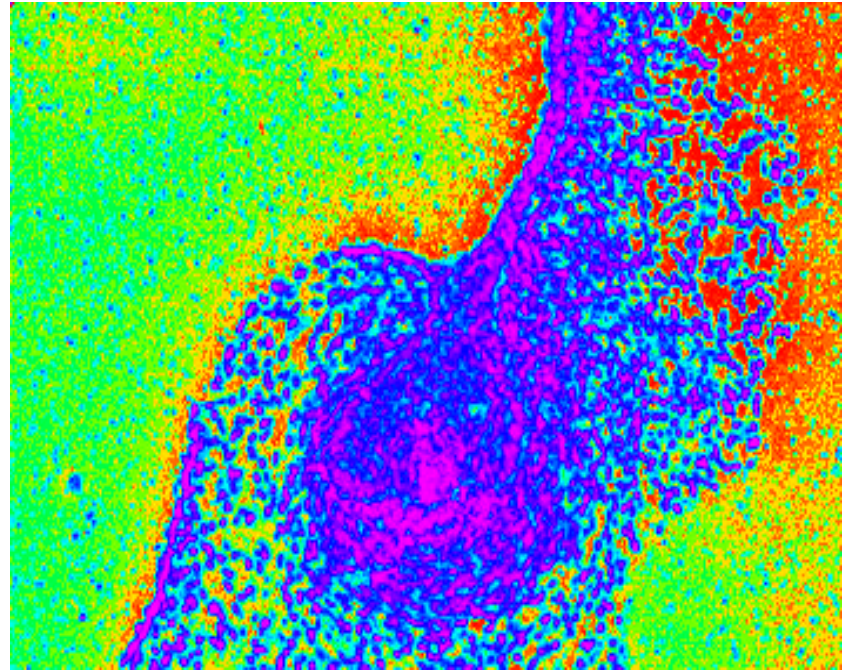
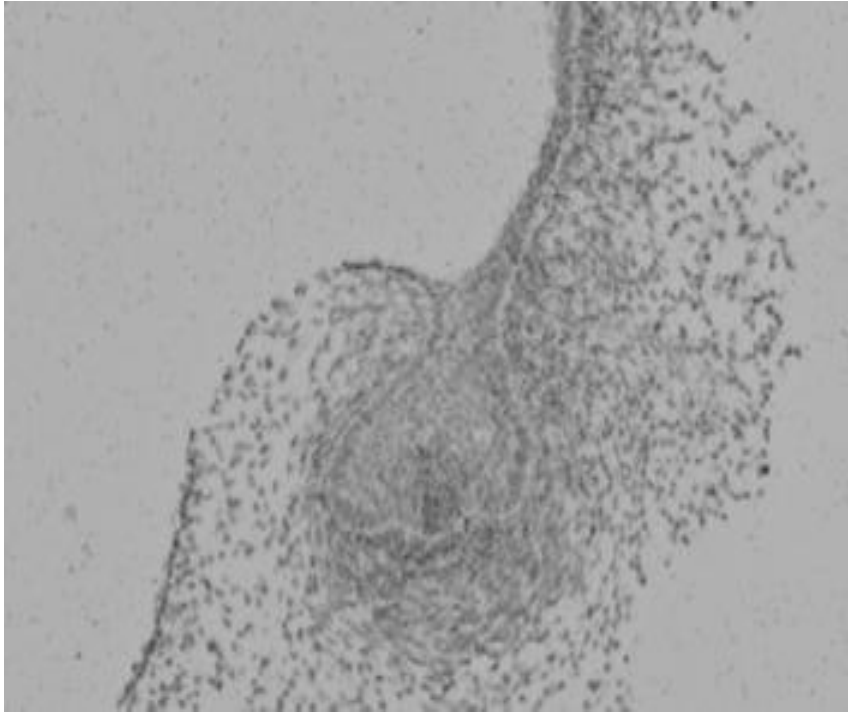


# Pseudo colour IP- examples



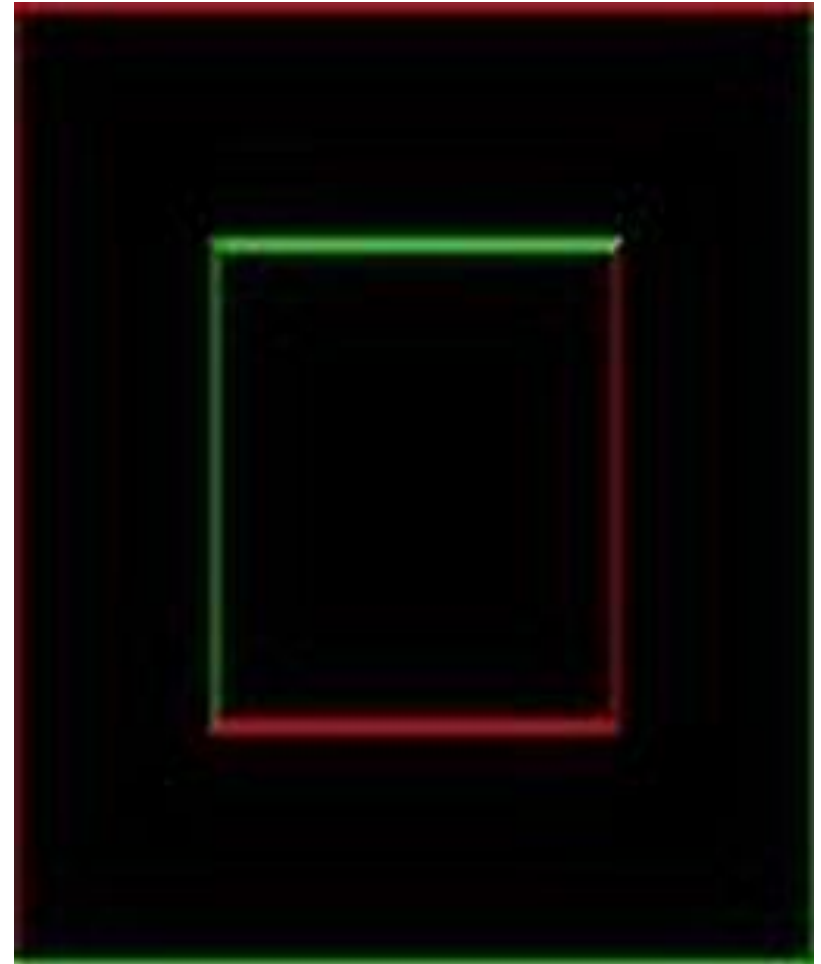
Grey scale - 2-colour mapping

# Pseudo colour IP- examples



Grey scale - multi-colour mapping

# Pseudo colour IP- edge map



**green:** white to black transition

**Red:** black to white transition in raster scan



# Full colour IP

colour image  $\rightarrow$  colour image

vector valued fn  $\rightarrow$  vector valued fn

$$\mathbf{I}: \mathbb{Z}^2 \rightarrow \mathbb{Z}^3 \quad c[m, n] = \begin{bmatrix} c_1[m, n] \\ c_2[m, n] \\ c_3[m, n] \end{bmatrix} \quad \text{3 components / colour planes}$$

**Strategy 1: Operating in the scalar space.**

All operations introduced for greyscale images can be applied to each of the greyscale image

# Full colour processing- strategy 1

## Options

1. Do identical operation in all 3 planes and combine results
  - Can lead to colour shifts
  
2. Process the ‘appropriate’ plane and combine
  - may or may not necessarily achieve the right effect
  - how to find the ‘appropriate’ plane?
    - depends on the task

# Full colour processing – **Strategy 1**

Examples:

- contrast stretching
- denoising
- sharpening

# Example 1: contrast stretching



Original



Histogram equalisation done on  
R,G and B planes

# Example 2: Enhancement

## Method

- Model the input image as

$$I = I_o S_M + S_A$$

contrast      luminosity

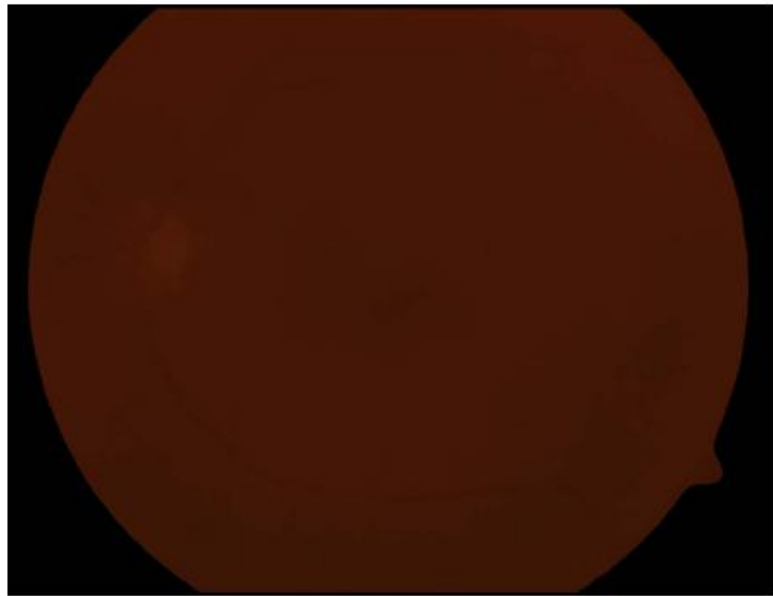
- Estimate the background
- Estimate  $S_M$  and  $S_A$  from the background
- Find  $I_o = (I - S_A)/S_M$

Input image



(a)

Result of same operation applied to R,G,B



(b)



(c)



(d)

Result of enhancing S and I channels independently

Result of operating on G and then reflecting it on G and B

# Handling colour

## Method1:

- Apply the method on  $r, g$  and  $b$  and normalise

## Method 2:

- Apply the method to the  $g$  plane and find  $g_{corr}$
- Next, find the desired colour image as

$$\hat{r} = \frac{g_{corr}}{v} * r, \quad \hat{g} = \frac{g_{corr}}{v} * g, \quad \hat{b} = \frac{g_{corr}}{v} * b, \quad v = \max[r, g, b]$$

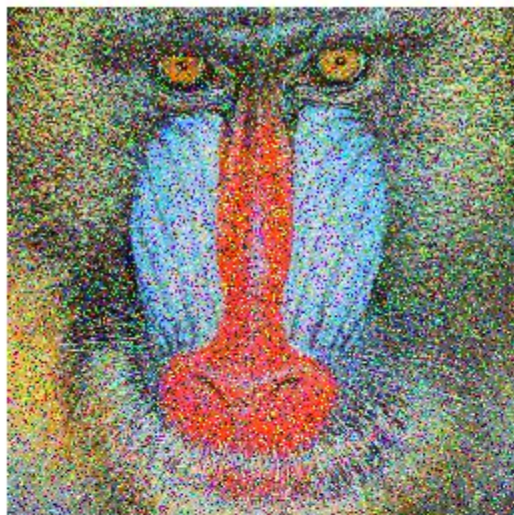
# Example 3: denoising

$$c[m, n] = \begin{bmatrix} c_1[m, n] \\ c_2[m, n] \\ c_3[m, n] \end{bmatrix} \text{ is a point in a 3-D space}$$

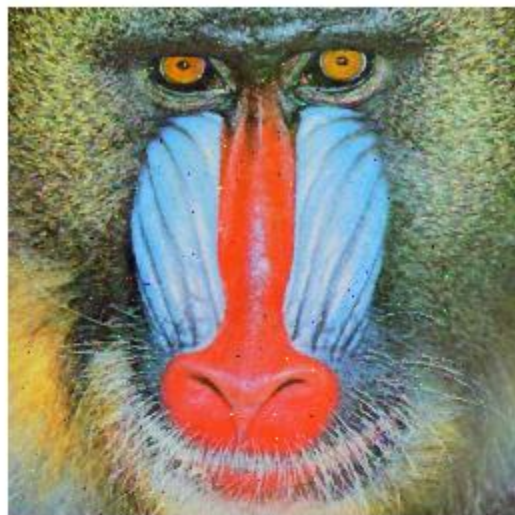
**Example:** median filtering for denoising impulse noise



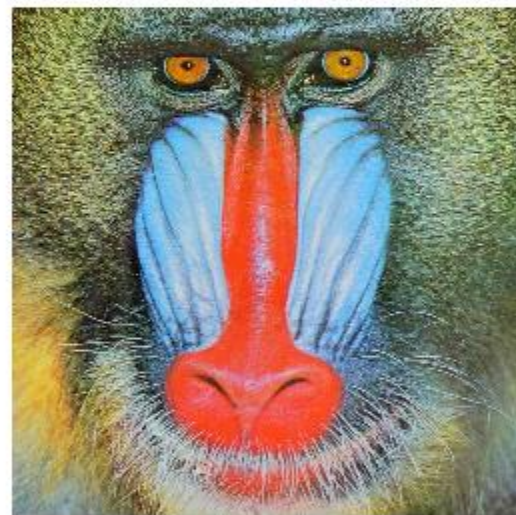
noise in rgb



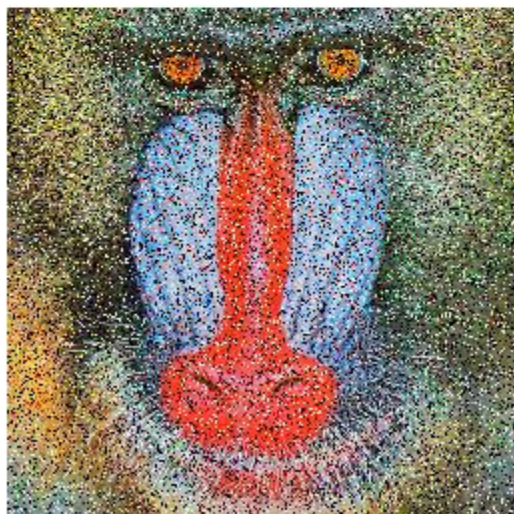
denoised in rgb



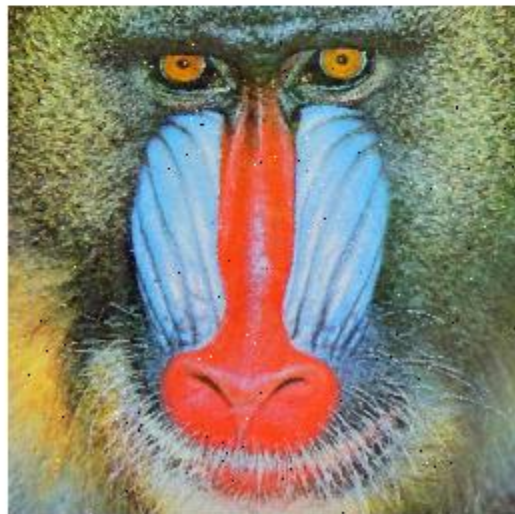
original



noise in hsi



denoised in hsi



# Sharpening- example

Sharpening of an image can be achieved by using a Laplacian as follows:

Given  $\{c_i(m,n)\}$  its Laplacian can be found as

$$\nabla^2[c(m,n)] = [\nabla^2 c_1(m,n) \quad \nabla^2 c_2(m,n) \quad \nabla^2 c_3(m,n)]^T$$

The required sharpened image

$$y(m,n) = c(m,n) + \alpha \nabla^2[c(m,n)]$$

## Strategy 2: Full colour processing

- operating on the vector space

# Ex 1. denoising

- Denoising by median filtering in vector space
  - to remove impulse noise

## **General method:**

- Consider all 3 colour components and rank order the vectors
  - Ranking is done on the distance between the centre and all neighbouring pixels
- Centre pixel is then replaced with the colour corresponding to the min distance value

# Magnified view of results

rgb



original



hsi



vmf (on multicolour space)

# Ex. 2: finding intensity transitions

**Example 2:** Transitions in intensity can be found using gradients

Gradient of a scalar valued  $f$  is a vector

$$\nabla f = \vec{g} = \begin{bmatrix} f_x \\ f_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

Of interest are its

- strength (magnitude)  $|\vec{g}|^2 = (f_x^2 + f_y^2)$
- direction  $\angle g = \tan^{-1}\left(\frac{f_y}{f_x}\right)$



# Gradient – colour images

What is the gradient of a vector-valued function  
 $c(x,y)$ ?

# Gradient – colour images

- $c(x,y) : \mathbb{R}^2 \rightarrow \mathbb{R}^3$       ex. RGB image

**Simple solution:** take the vector sum of the gradients in each channel

$$\overrightarrow{g_c} = \overrightarrow{g_R} + \overrightarrow{g_G} + \overrightarrow{g_B}$$

- Computationally cheap
- May not reflect true scenario
  - Ex. B channel has no variation; R and G have equal variation along  $x$  direction but in opposite direction (left to right vs right to left) will lead to

$$\left| \overrightarrow{g_c} \right| = g_{R_x} - g_{G_x} = 0$$



# Gradient - colour image

$$\vec{c}(x, y) = \begin{bmatrix} c_1(x, y) \\ c_2(x, y) \\ c_3(x, y) \end{bmatrix}$$

**Better option:** Use the gradient generalisation

$$c(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R}^3$$

$\therefore$  gradient of  $c$  is a **tensor** i.e. its Jacobian matrix  $_{2 \times 3}$

$$J = \begin{bmatrix} \frac{\partial c_1}{\partial x} & \frac{\partial c_2}{\partial x} & \frac{\partial c_3}{\partial x} \\ \frac{\partial c_1}{\partial y} & \frac{\partial c_2}{\partial y} & \frac{\partial c_3}{\partial y} \end{bmatrix} = \begin{bmatrix} \frac{\partial \vec{c}}{\partial x} \\ \frac{\partial \vec{c}}{\partial y} \end{bmatrix} = \begin{bmatrix} \vec{c}_x \\ \vec{c}_y \end{bmatrix}$$

Note: when  $f$  is scalar valued, this becomes the gradient vector

# Gradient ..contd.

Of interest:

At every point  $(x,y)$  we would like to know

1. The direction  $\theta$  in which maximum change is occurring in  $c$ 
  - Gradient direction
2. The magnitude of this maximum change
  - Gradient magnitude

## Define tensor components

$$g_{xx} = \langle \vec{c}_x, \vec{c}_x \rangle = \vec{c}_x^T \vec{c}_x = \left| \frac{\partial c_1}{\partial x} \right|^2 + \left| \frac{\partial c_2}{\partial x} \right|^2 + \left| \frac{\partial c_3}{\partial x} \right|^2$$

$$g_{yy} = \langle \vec{c}_y, \vec{c}_y \rangle = \vec{c}_y^T \vec{c}_y = \left| \frac{\partial c_1}{\partial y} \right|^2 + \left| \frac{\partial c_2}{\partial y} \right|^2 + \left| \frac{\partial c_3}{\partial y} \right|^2$$

$$g_{xy} = \langle \vec{c}_x, \vec{c}_y \rangle = \vec{c}_x^T \vec{c}_y = \frac{\partial c_1}{\partial x} \frac{\partial c_1}{\partial y} + \frac{\partial c_2}{\partial x} \frac{\partial c_2}{\partial y} + \frac{\partial c_3}{\partial x} \frac{\partial c_3}{\partial y}$$

# Gradient of a colour image

Magnitude of the gradient at  $(x,y)$

$$A_{\theta}(x, y) = \sqrt{\frac{1}{2}[(g_{xx} + g_{yy}) + (g_{xx} - g_{yy}) \cos 2\theta + 2g_{xy} \sin 2\theta]}$$

Direction of the gradient at  $(x,y)$

$$\theta(x, y) = \frac{1}{2} \tan^{-1} \left[ \frac{2g_{xy}}{g_{xx} - g_{yy}} \right]$$

Note: In practice,

- each of these derivatives are computed with a mask
- $\theta$  and  $F_{\theta}$  are images of same size as  $c(x,y)$

What do we gain with this formulation?

# Example 1

An RGB image with

- No variation in  $y$  direction in RGB planes;  $\Rightarrow \vec{c}_y = 0$
- B is constant :  $B_x = B_y = 0$
- R and G have equal gradients in  $x$  direction but of opposite sign:  $R_x = -G_x$

$$\therefore g_{xy} = g_{yy} = 0; \quad g_{xx} = 2|R_x|^2$$

$$\theta = \tan^{-1}(0) \Rightarrow \theta = 0 \quad \text{or} \quad \frac{\pi}{2}$$

$$A_0 = \sqrt{g_{xx}} = \sqrt{2}|R_x|$$

**Check:** What will you get if you compute using the vector sum of gradients?

# Example 2

RGB image with equal variation in both  
directions in all planes  $\Rightarrow g_{xx} = g_{yy} = g_{xy} = a$

$$\therefore \theta = \frac{1}{2} \tan^{-1} \left( \frac{2a}{a-a} \right) = \pm \frac{\pi}{4}$$

$$A_{\frac{\pi}{4}} = \sqrt{2a}$$

**Check:** What will you get if you compute  
using the vector sum of gradients?

# Summary

- Processing colour images by treating them as vector valued functions can be advantageous
  - But computationally expensive
- Degree of effectiveness depends on the task
  - In edge detection, 90% detection is possible by processing only the *intensity* plane
  - Is the additional 10% is critical enough to justify more computations?
    - Depends on appln. domain