Universität Hamburg
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MIN-Fakultät
Fachbereich Informatik
Arbeitsbereich SAV/BV (KOGS)

Image Processing 1 (IP1)
Bildverarbeitung 1

Lecture 3 – Image Understanding and Image Formation

Winter Semester 2015/16

Slides: Prof. Bernd Neumann
Slightly revised by: Dr. Benjamin Seppke & Prof. Siegfried Stiehl

Definition of Image Understanding

Image understanding is the task-oriented reconstruction and interpretation of a scene by means of images

- "scene": section of the real world
  - stationary (3D) or
  - moving (4D)
- "image": view of a scene
  - projection, density image (2D)
  - depth image (2 1/2D)
  - image sequence (3D)
- "reconstruction and interpretation“: computer-internal scene description
  - Quantitative
  - Qualitative
  - Symbolic
- "task-oriented": for a purpose, to fulfil a particular task
  - context-dependent,
  - supporting actions of an agent

Illustration of Image Understanding

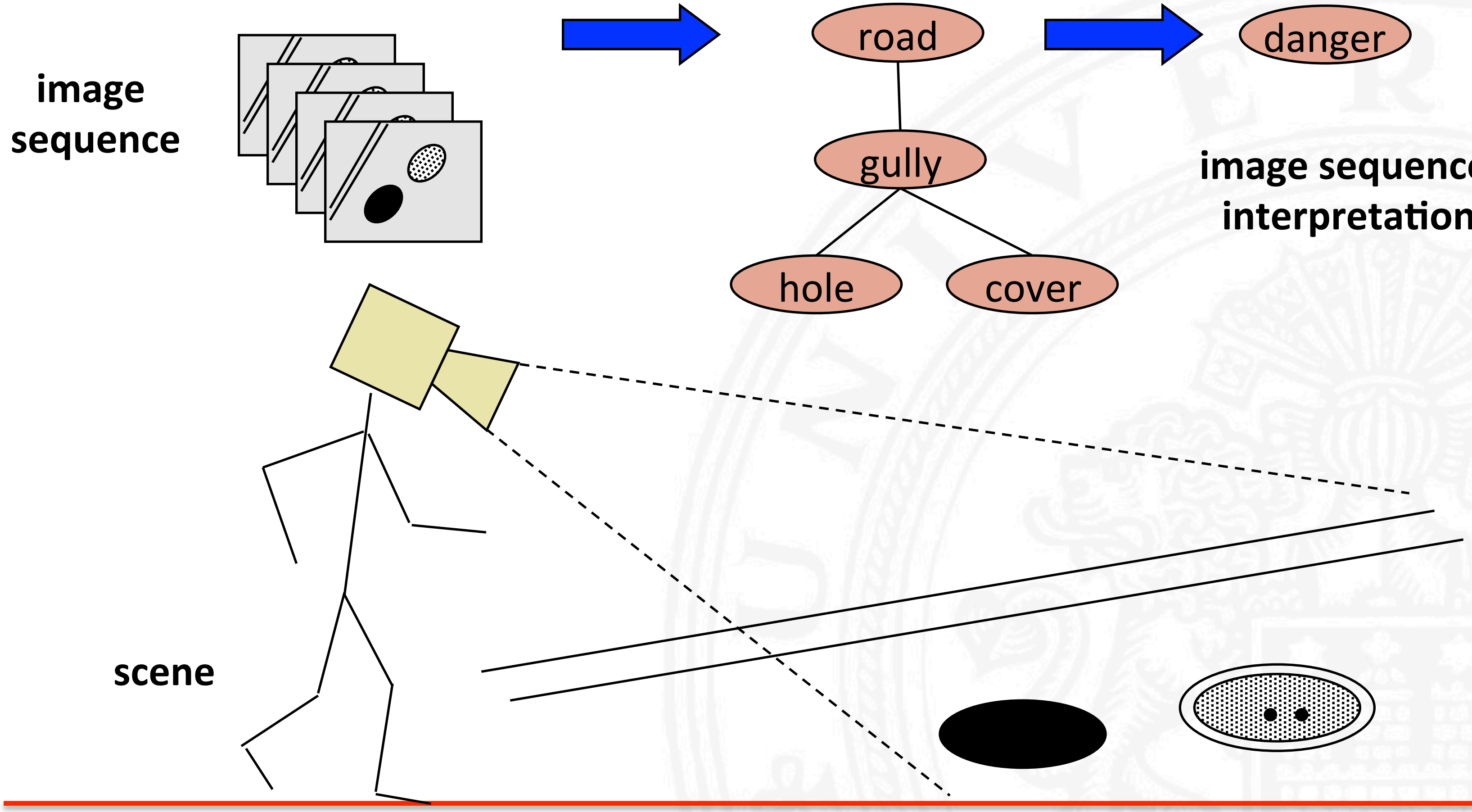


image sequence

road

gully

hole

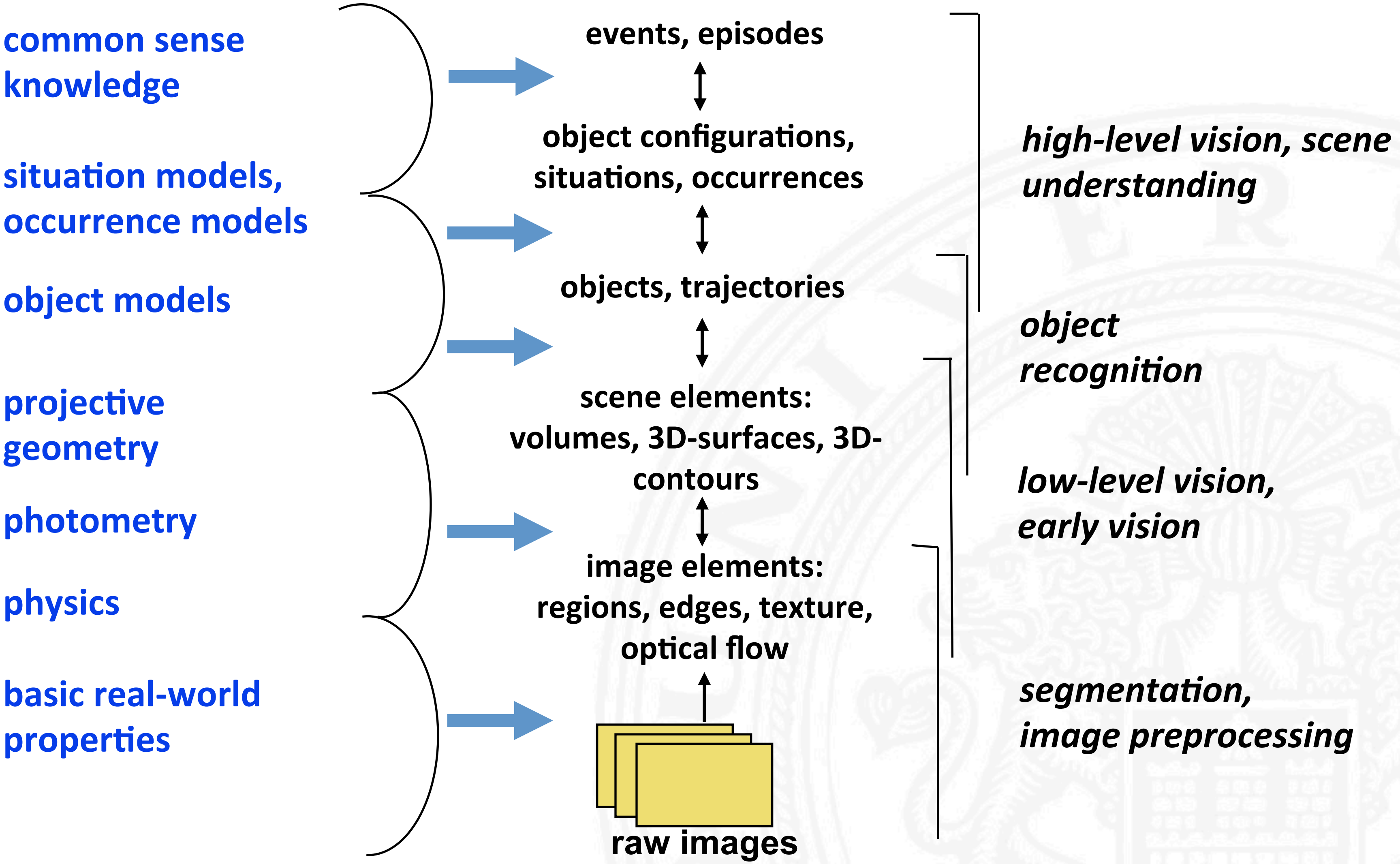
cover

danger

image sequence interpretation

scene

Image Understanding as a Knowledge-based Process



common sense knowledge

situation models, occurrence models

object models

projective geometry

photometry

physics

basic real-world properties

events, episodes

↕

object configurations, situations, occurrences

↕

objects, trajectories

↕

scene elements: volumes, 3D-surfaces, 3D-contours

↕

image elements: regions, edges, texture, optical flow

↑

raw images

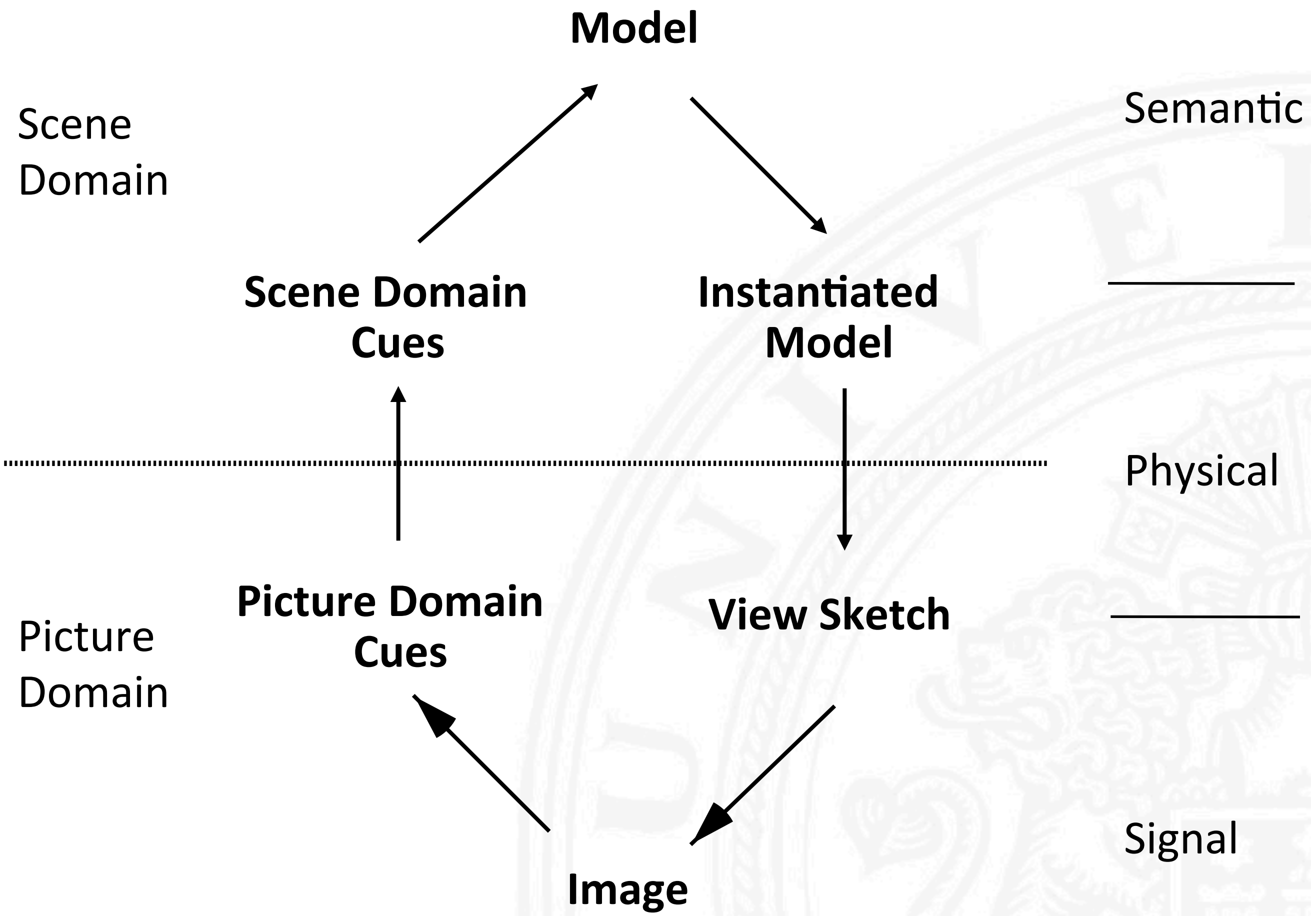
high-level vision, scene understanding

object recognition

low-level vision, early vision

segmentation, image preprocessing

A Model of Scene Analysis (Kanade 78)



Abstraction Levels for the Description of Computer Vision Systems

Knowledge level

What knowledge or information enters a process? What knowledge or information is obtained by a process?

What are the laws and constraints which determine the behavior of a process?

Algorithmic level

How is the relevant information represented?

What algorithms are used to process the information?

Implementation level

What programming language is used?

What computer hardware is used?

Example for Knowledge-level Analysis

What knowledge or information enters a process? What knowledge or information is obtained by a process?

What are the laws and constraints which determine the behavior of a process?

- Consider shape-from-shading:

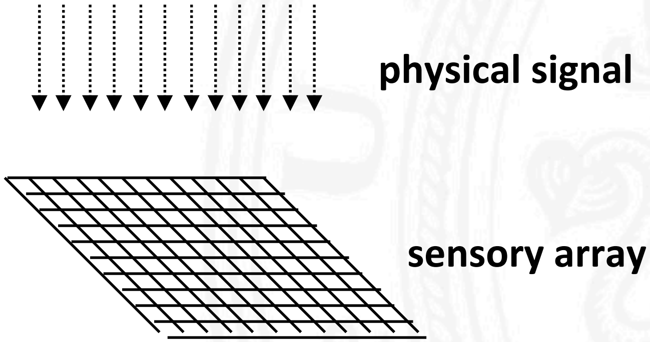
In order to obtain the 3D shape of an object, it is necessary to:

- state what knowledge is available (greyvalues, surface properties, illumination direction, etc.)
- state what information is desired (e.g. qualitative vs. quantitative)
- exploit knowledge about the physics of image formation

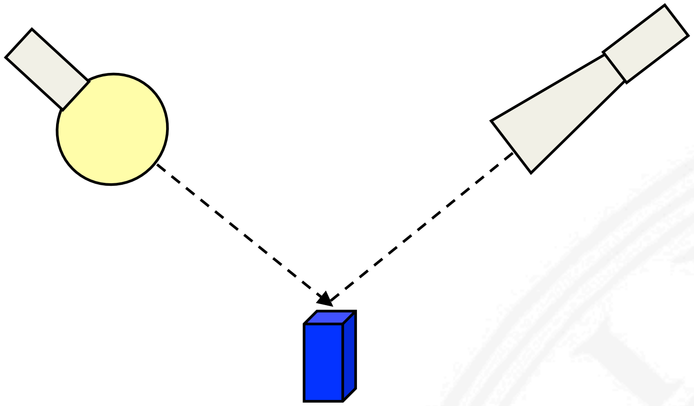
Image Formation

Images can be generated by various processes:

- Illumination of surfaces, measurement of reflections ⇦ **Natural Images**
- Illumination of translucent material, measurement of irradiation
- measurement of heat (infrared) radiation
- X-ray of material, computation of density map
- measurement of any features by means of a sensory array



Formation of Natural Images



Intensity (brightness) of a pixel depends on

1. illumination (spectral energy, secondary illumination)
2. object surface properties (reflectivity)
3. sensor properties
4. geometry of light-source, object and sensor constellation (angles, distances)
5. transparency of irradiated medium (mistiness, dustiness)

Qualitative Surface Properties

When light hits a surface, it may be

- absorbed
- Reflected
- scattered

} in general, all effects may be mixed

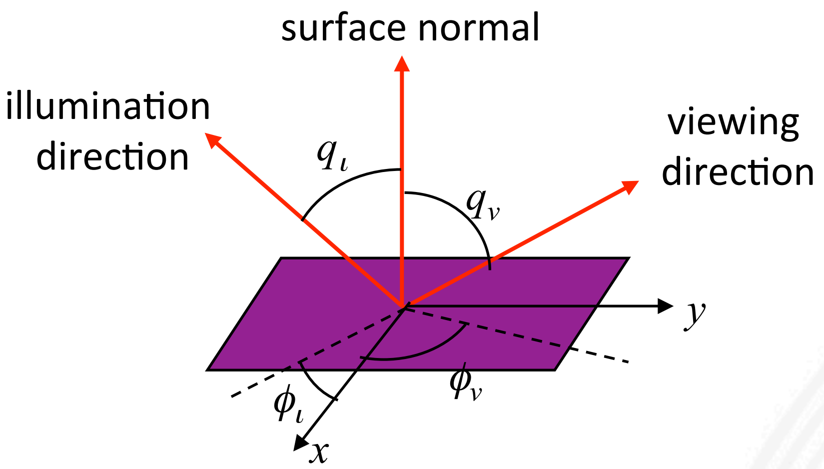
Simplifying assumptions:

- Radiance leaving at a point is due to radiance arriving at this point
- All light leaving the surface at a wavelength is due to light arriving at the same wavelength
- Surface does not generate light internally

The "amount" of reflected light may depend on:

- the "amount" of incoming light
- the angles of the incoming light w.r.t. to the surface orientation
- the angles of the outgoing light w.r.t. to the surface orientation

Photometric Surface Properties



q_ι, q_v	polar (zenith) angles
ϕ_ι, ϕ_v	azimuth angles

In general, the ability of a surface to reflect light is given by the Bi-directional Reflectance Distribution Function (BRDF) *r*:

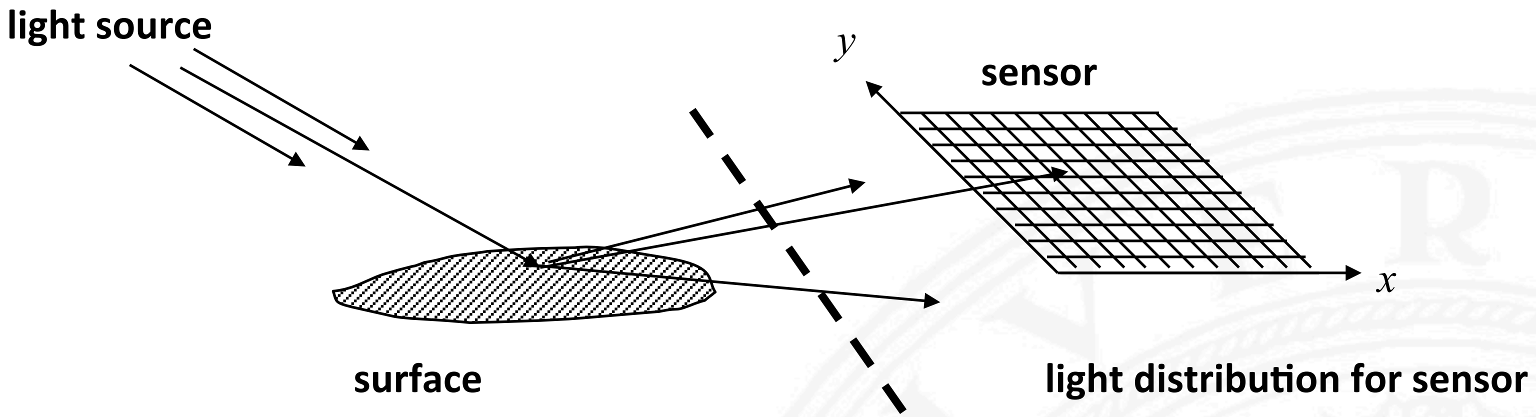
$$r(\theta_l,\phi_l\,;\theta_v,\phi_v) = \frac{\delta_L(\theta_v,\phi_v)}{\delta_E(\theta_l,\phi_l)}$$

radiance of surface patch towards viewer

irradiance of light source received by the surface patch

For many materials the reflectance properties are rotation invariant, in this case the BRDF depends on q_ι, q_v, ϕ, where $\phi = \phi_\iota - \phi_v$.

Intensity of Sensor Signals



Intensities of sensor signals depend on

- location x, y on sensor plane
- instance of time t
- frequency of incoming light wave λ
- spectral sensitivity of sensor

$$f(x,y\underset{\infty}{,}t) = \int_0^\infty C(x,y,t,\lambda)S(\lambda)\,d\lambda$$

sensitivity function of sensor

spectral energy distribution

Multispectral Images

- Sensors with n separate channels of different spectral sensitivities generate multispectral images:

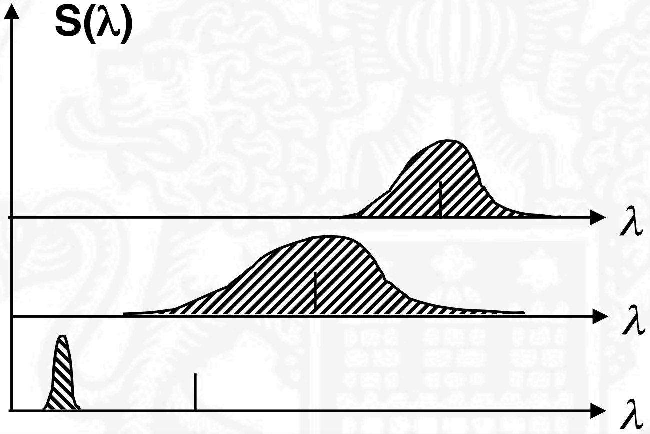
$$f_1(x,y,t) = \int_0^\infty C(x,y,t,\lambda) S_1(\lambda)\, d\lambda$$

$$f_2(x,y,t) = \int_0^\infty C(x,y,t,\lambda) S_2(\lambda)\, d\lambda$$

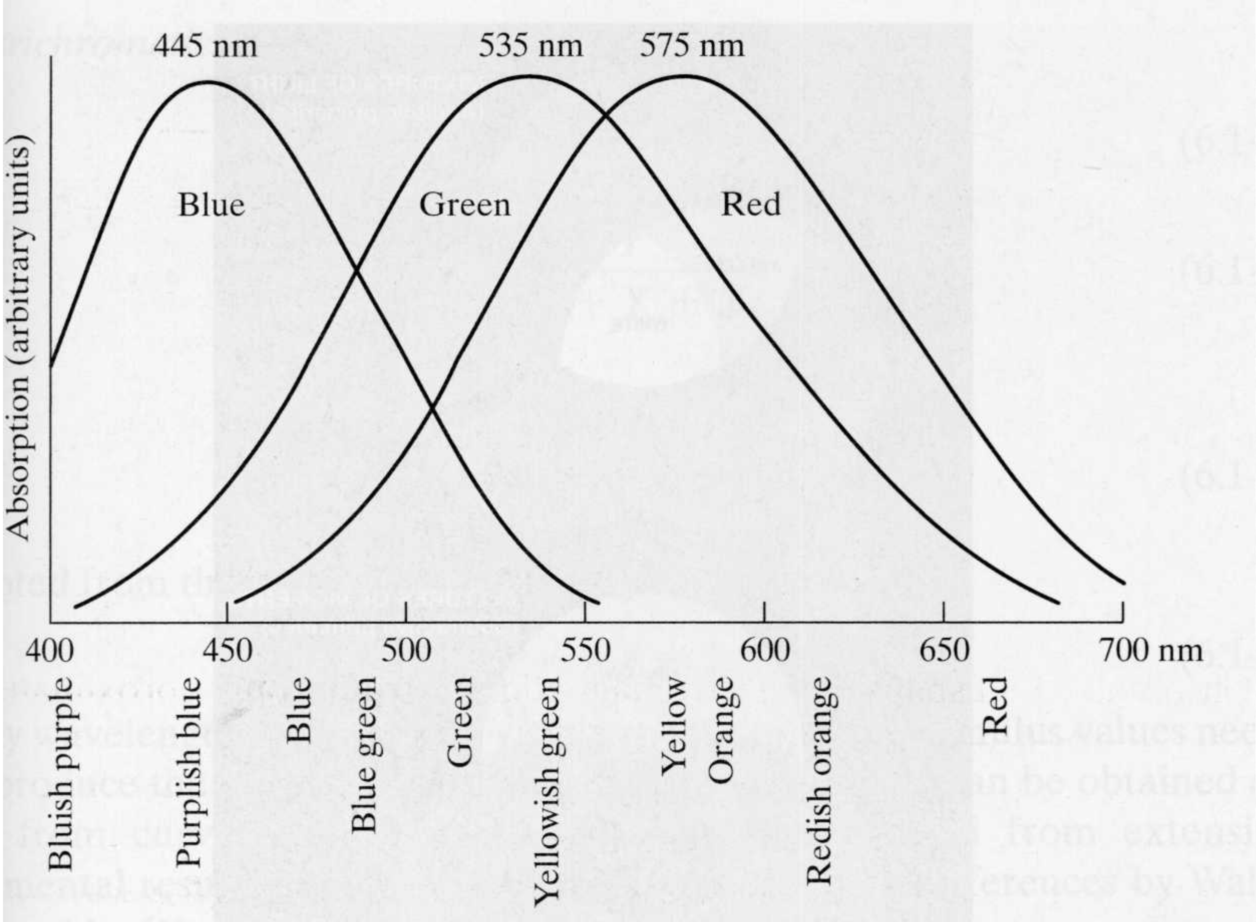
$$\vdots$$

$$f_n(x,y,t) = \int_0^\infty C(x,y,t,\lambda) S_n(\lambda)\, d\lambda$$

- Example:
  - R (red) 650 nm center frequency
  - G (green) 530 nm center frequency
  - B (blue) 410 nm center frequency



Spectral Sensitivity of Human Eyes



Standardized wavelengths: red = 700 nm, green = 546.1 nm, blue = 435.8 nm

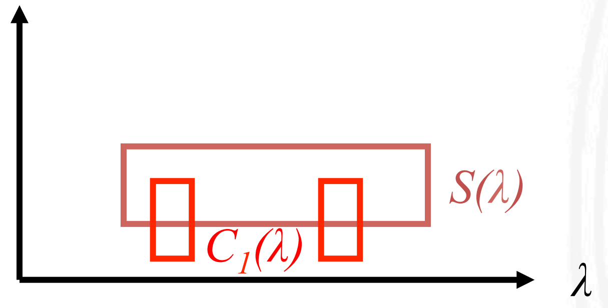
Non-unique Sensor Response

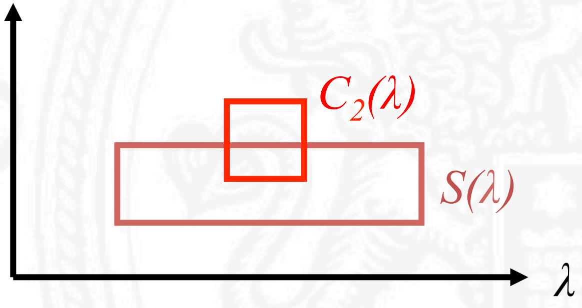
Different spectral distributions may lead to identical sensor responses and hence cannot be distinguished

$$f_1(x,y,t) = \int_0^\infty C_1(x,y,t,\lambda) S(\lambda)\, d\lambda = \int_0^\infty C_2(x,y,t,\lambda) S(\lambda)\, d\lambda$$

different spectral energy distributions

Example:





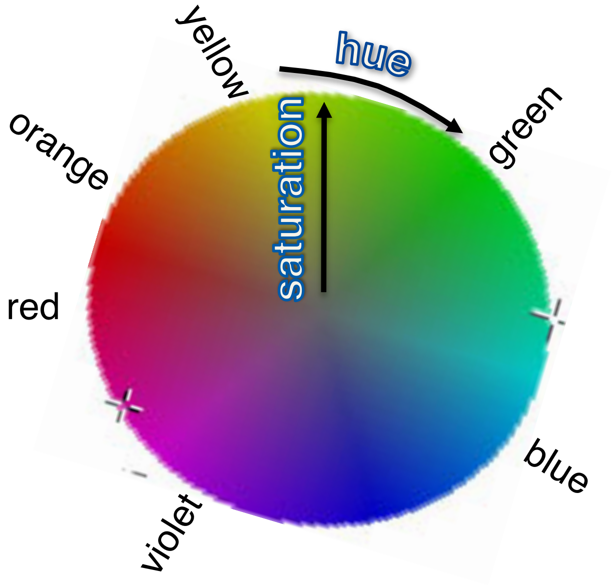
Dimensions of Colour

Human perception of colour distinguishes between 3 dimensions:

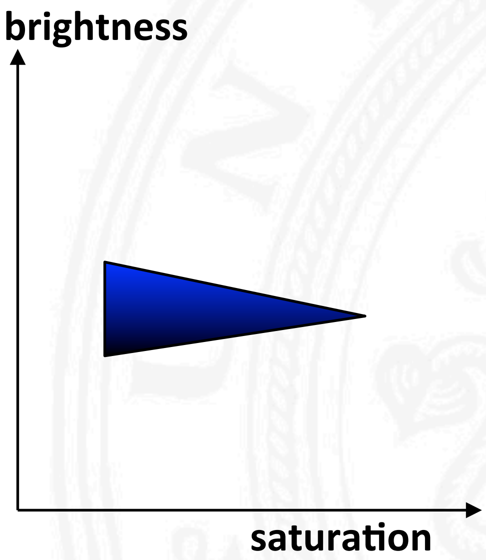
- Hue } chromaticity
- Saturation } chromaticity
- Brightness

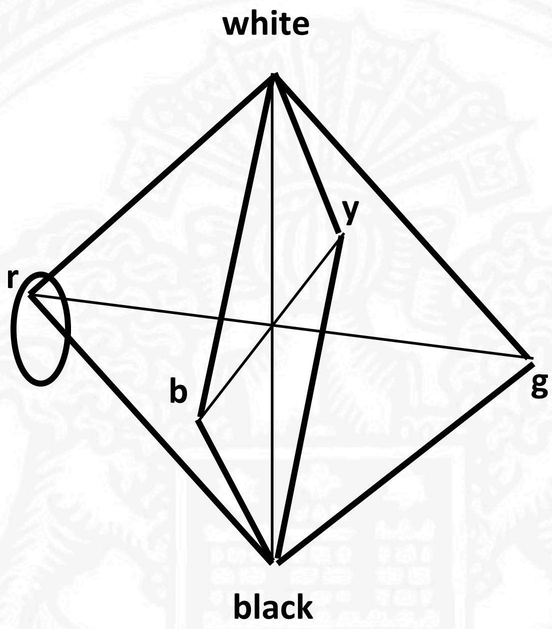
NCS* colour spindle

* Swedish Natural Colour System



colour circle

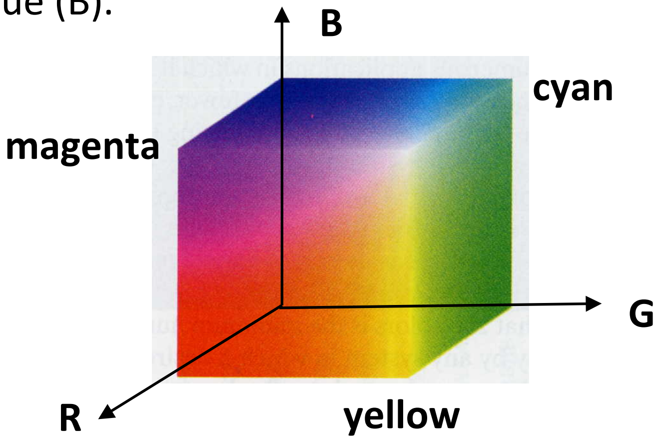




Computer Vision Colour Models

RGB colour model

Different colors are generated by adding different portions of red (R), green (G), and blue (B).



RGB is the most commonly used color space in Computer Vision.

Typical discretization:

8 bits per colour dimension

→ 16.777.216 colours

HSI colour model

Different colors are described by Hue (H), Saturation (S), and Intensity (I). Can be derived from RGB model:

$$H = \begin{cases} Q & \text{if} \quad B \le G \\ 360 - Q & \text{if} \quad B > G \end{cases}$$

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

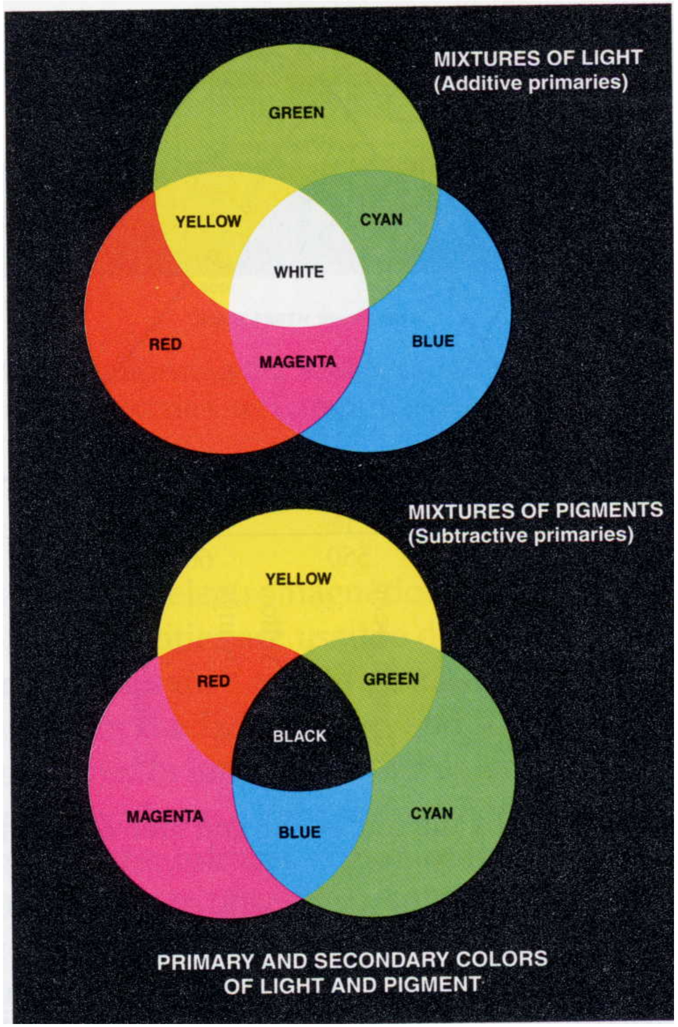
$$S = 1 - \frac{3}{R+G+B}\min(R,G,B)$$

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

Closer to human perception

Better choice e.g. for selecting colors!

Primary and Secondary Colours



Primary colours:

red, green, blue

Secondary colours:

magenta = red + blue
cyan = green + blue
yellow = red + green

from: Gonzales & Woods
Digital Image Processing
Prentice-Hall 2002

RGB Images of a Natural Scene

Here, single colour images are rendered as greyvalue intensity images:

stronger spectral intensity = more brightness

R+G+B

R

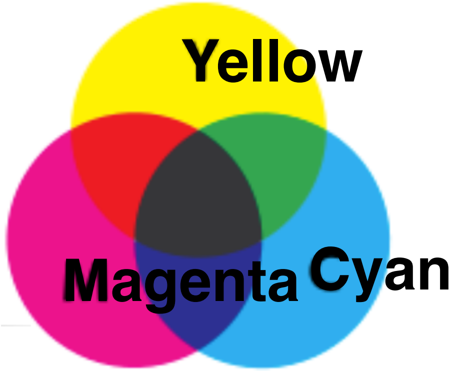
G

B

Printing Color Models

Subtractive color model because of white background!

CMY colour model



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

CMYK colour model

A combination of C, M, and Y typically cannot produce a clear, dark black. Therefore a fourth black ink (K for 'key' or blac'k') is used in addition.

Discretization of Images

Image functions must be discretized for computer processing:

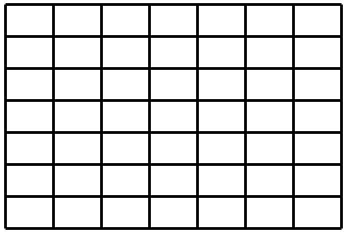
- spatial quantization
  the image plane is represented by a 2D array of picture cells
- greyvalue quantization
  each greyvalue is taken from a discrete value range
- temporal quantization
  greyvalues are taken at discrete time intervals

$$f(x,y,t) \Rightarrow \begin{Bmatrix} f_s(x_1, y_1,t_1), & f_s(x_2, y_2,t_1), f_s(x_3, y_3,t_1), & \ldots \\ f_s(x_1, y_1,t_2), & f_s(x_2, y_2,t_2), f_s(x_3, y_3,t_2), & \ldots \\ f_s(x_1, y_1,t_3), & f_s(x_2, y_2,t_3), f_s(x_3, y_3,t_3), & \ldots \end{Bmatrix}$$

A single value of the discretized image function is called a pixel (picture element).

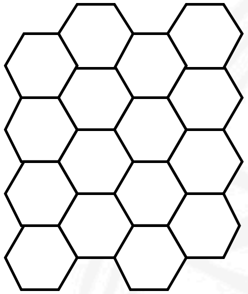
Spatial Quantization

Rectangular grid

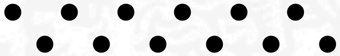


Greyvalues represent the quantized value of the signal power falling into a grid cell.

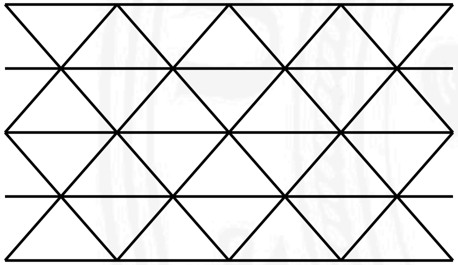
Hexagonal grid



Note that samples of a hexagonal grid are equally spaced along rows, with successive rows shifted by half a sampling interval.

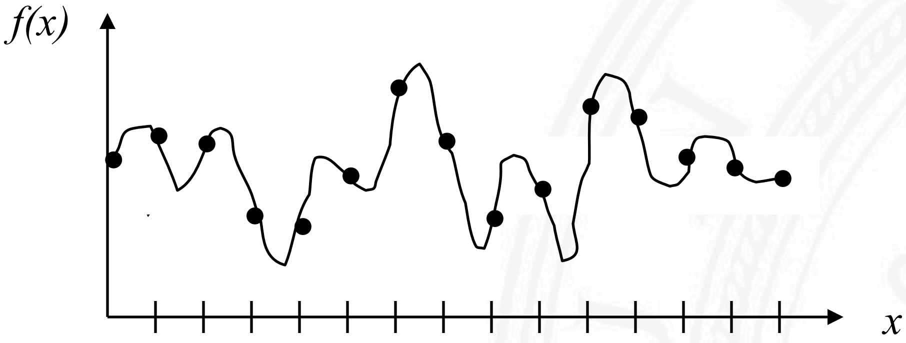


Triangular grid



Reconstruction from Samples

- Under what conditions can the original (continuous) signal be reconstructed from its sampled version?
- Consider a 1-dimensional function *f(x)*:



- Reconstruction is only possible, if "variability" of function is restricted.

Sampling Theorem

Shannon´s Sampling Theorem:

A bandlimited function with bandwidth W can be exactly reconstructed from equally spaced samples, if the sampling distance is not larger than $\frac{1}{2W}$.

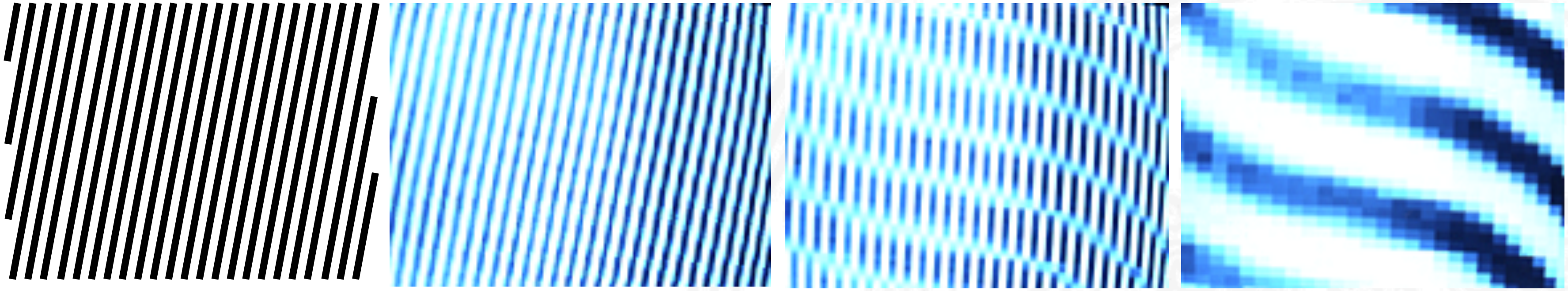
Bandwidth = largest frequency contained in signal
(=> Fourier decomposition of a signal)

Analogous theorem holds for 2D signals with limited spatial frequencies W_x and W_y

Aliasing

Sampling an image with fewer samples than required by the sampling theorem may cause "aliasing" (artificial structures).

Example:



original **143 x 128** **71 x 64** **35 x 32**

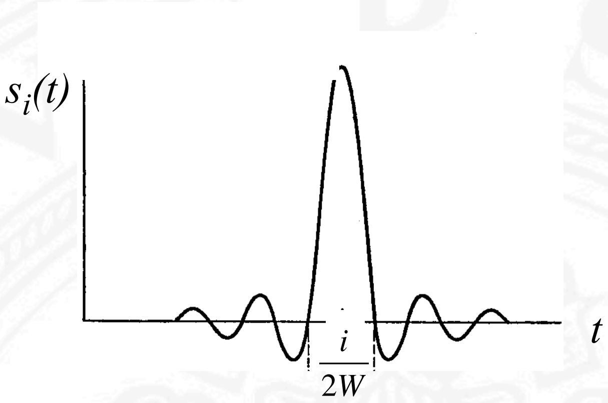
To avoid aliasing, bandwidth of image must by reduced prior to sampling (=> low-pass filtering)

Reconstructing the Image Function from Samples

Formally, a continuous function *f(t)* with bandwidth *W* can be exactly reconstructed using sampling functions $s_i(t)$:

$$s_i(t) = \sqrt{2W}\,\frac{\sin 2\pi W\left[t - i/(2W)\right]}{2\pi W\left[t - i/(2W)\right]}$$

$$x(t) = \sum_{i=-\infty}^{\infty} \sqrt{\frac{1}{2W}}\ \underbrace{\left(\frac{i}{2W}\right)}_{\textbf{sample values}}\ S_i(t)$$



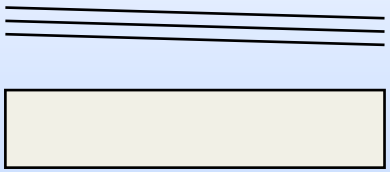
An analogous equation holds for 2D.

In practice, image functions are generated from samples by interpolation.

Sampling TV Signals

PAL standard:

- picture format 3 : 4
- 25 full frames (50 half frames) per second
- interlaced rows: 1, 3, 5, ... , 2, 4, 6, ...
- 625 rows per full frame, 576 visible
- 64 ms per row, 52 ms visible
- 5 MHz bandwidth



Only 1D sampling is required because of fixed row structure.

Sampling intervals of Dt = 1/(2W) = 10^{-7}s = 100 ns give maximal possible resolution.

With Dt = 100 ns, a row of duration 52 ms gives rise to 520 samples.

In practice, one often chooses 512 pixels per TV row.

→ 576 x 512 = 294912 pixels per full frame

→ rectangular pixel size with $\frac{width}{height} = \frac{\left(\frac{4}{512}\right)}{\left(\frac{3}{576}\right)} = 1.5$