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

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Illustration of Image Understanding

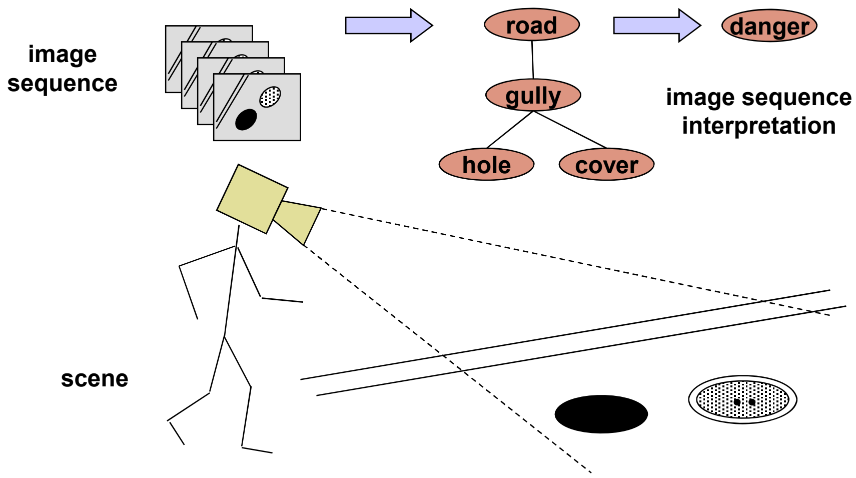

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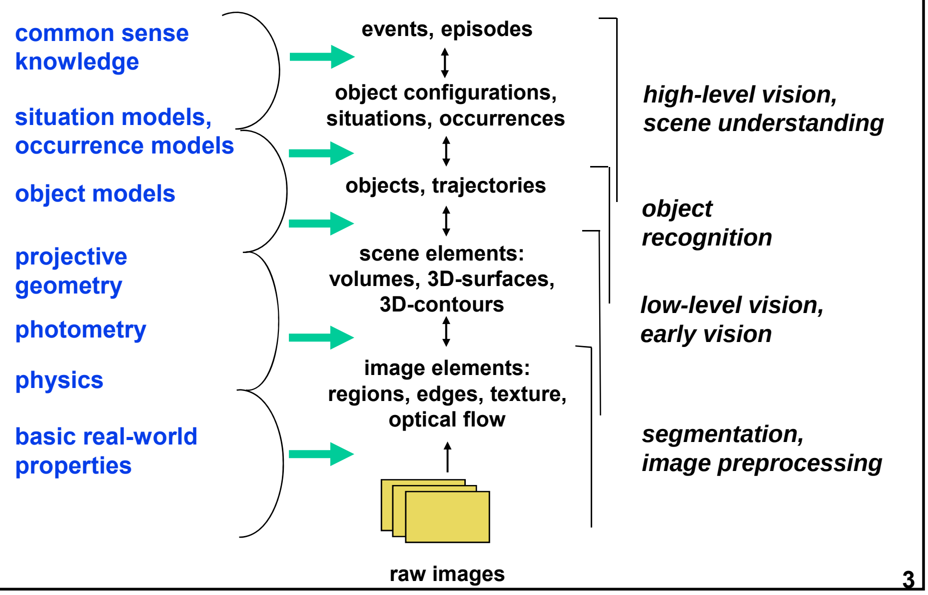
Image Understanding as a Knowledge-based Process



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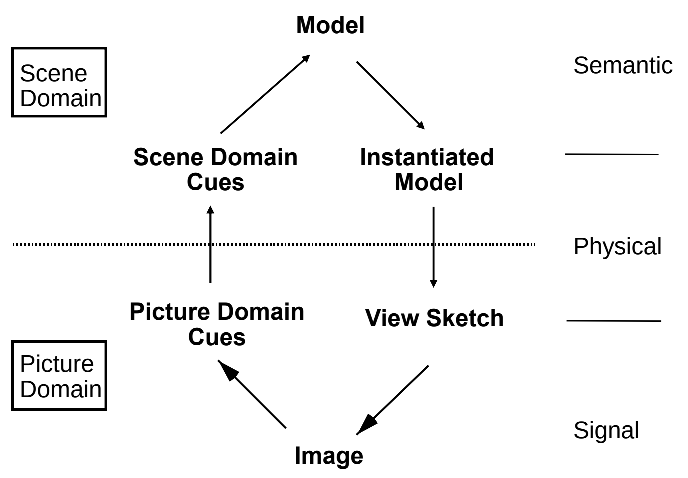
A Model of Scene Analysis (Kanade 78)



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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?

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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**

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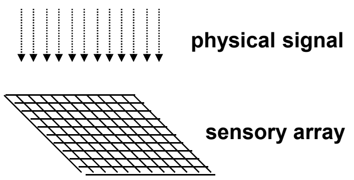
Image Formation

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



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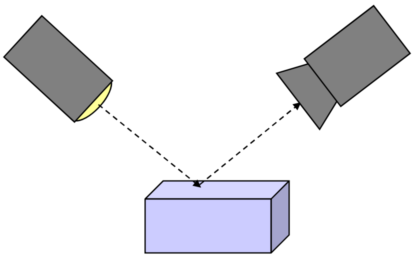
Formation of Natural Images



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)

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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

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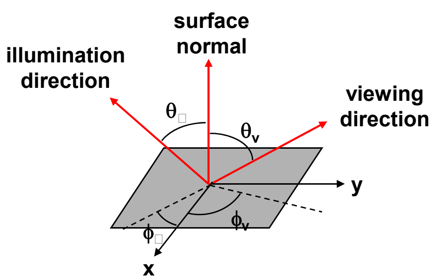
Photometric Surface Properties



$\theta_\square$, θ_v polar (zenith) angles

$\phi_\square$, 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:

$$r(\theta_i, \phi_i; \theta_v, \phi_v) = \frac{\delta L(\theta_v, \phi_v)}{\delta E(\theta_i, \phi_i)}$$

δE = irradiance of light source received by the surface patch

δL = radiance of surface patch towards viewer

For many materials the reflectance properties are rotation invariant, in this case the BRDF depends on $\theta_\square$, θ_v, ϕ, where□ϕ □ $\phi_\square$ - ϕ_v.

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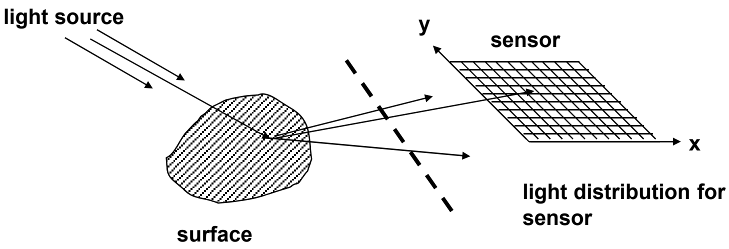
Intensity of Sensor Signals



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

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

$S(\lambda)$: sensitivity function of sensor

$C(x,y,t,\lambda)$: spectral energy distribution

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Multispectral Images

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

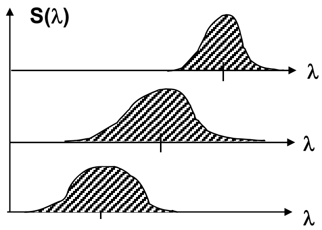
$$f_1(x,y,t) = \int_0^\infty C(x,y,t,\lambda) S_1(\lambda) d\lambda$$

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

$$f_3(x,y,t) = \int_0^\infty C(x,y,t,\lambda) S_3(\lambda) d\lambda$$

Example:

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



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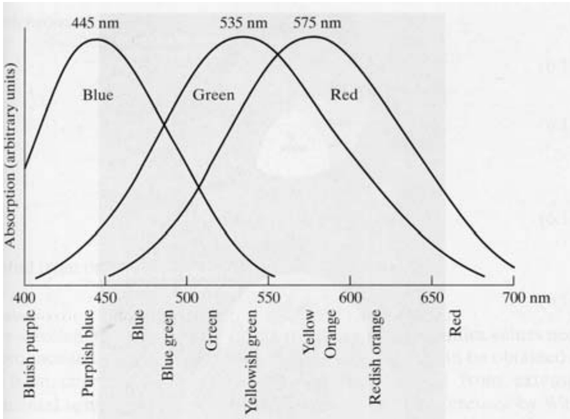
Spectral Sensitivity of Human Eyes



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

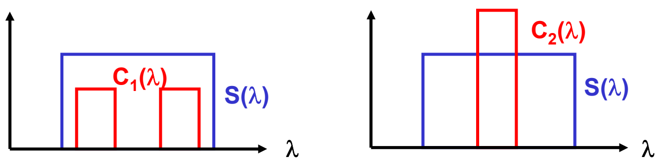
Non-unique Sensor Response

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

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

different spectral energy distributions

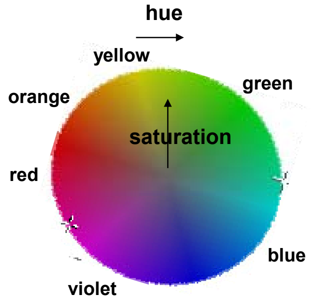
Example:



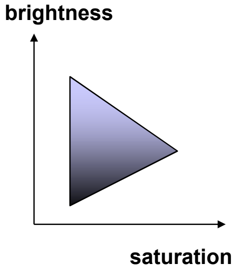
Dimensions of Colour

Human perception of colour distinguishes between 3 dimensions:
- hue
- saturation
- brightness

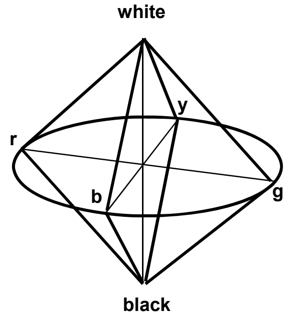
(hue and saturation } chromaticity)



colour circle



NCS* colour spindle



* Swedish Natural Colour System

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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

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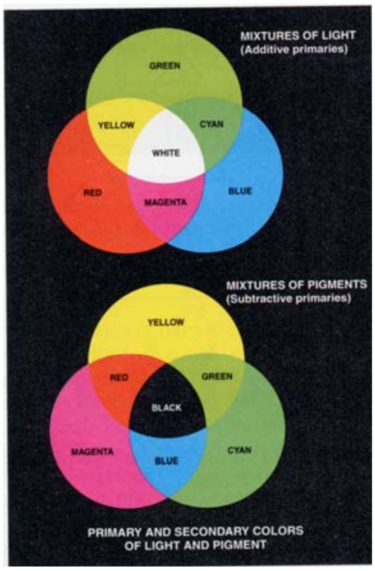
Primary and Secondary Colours



Primary colours:

red, green, blue

Secondary colours:

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

aus: Gonzales & Woods
Digital Image Processing
Prentice Hall 2002

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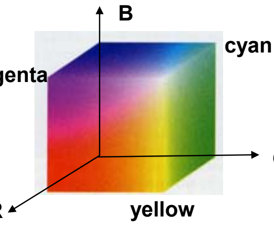
Technical Colour Models

RGB colour model



Typical discretization:

8 bits per colour dimension
=> 16.777.216 colours

CMY colour model

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

HSI colour model

Hue:

$$H = \begin{cases} \Theta & \text{if } B \leq G \\ 360 - \Theta & \text{if } B > G \end{cases}$$

$$\Theta = \cos^{-1} \frac{1/2\,[(R-G) + (R-B)]}{[(R-G)^2 + (R-B)(G-B)]^{1/2}}$$

Saturation:

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

Intensity:

$$I = 1/3\,(R + G + B)$$

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Discretization of Images

Image functions must be discretized for computer processing:

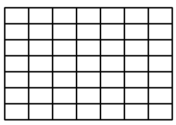
- **spatial quantization**
  the image plane is represented by a 2D array of picture cells
- **greyvalue quantization**
  each greyvalue is taken from a discrete value range
- **temporal quantization**
  greyvalues are taken at discrete time intervals

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

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

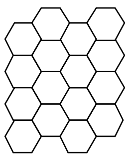
Spatial Quantization

Rectangular grid

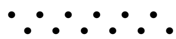


Greyvalues represent the quantized value of the signal power falling into a grid cell.

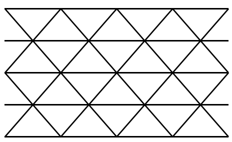
Hexagonal grid



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



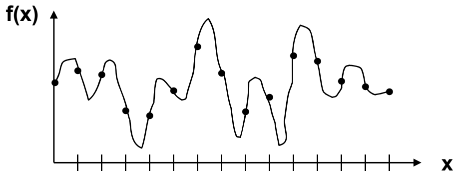
Triangular grid



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.

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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 $\frac{1}{2\,W}$

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

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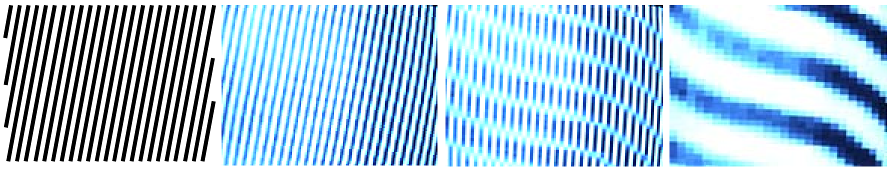
Aliasing

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)

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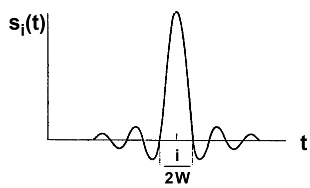
Reconstructing the Image Function from Samples

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

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

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



An analogous equation holds for 2D.

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

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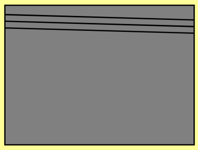
Sampling TV Signals

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 µs per row, 52 µs visible
- 5 MHz bandwidth



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

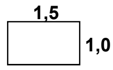
Sampling intervals of $\Delta t = 1/(2W) = 10^{-7}$s = 100 ns give maximal possible resolution.

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

In practice, one often chooses <u>512 pixels per TV row</u>.

=> 576 x 512 = 294912 pixels per full frame

=> rectangular pixel size with width/height $=(\frac{4}{512}) / (\frac{3}{576}) = 1{,}5$



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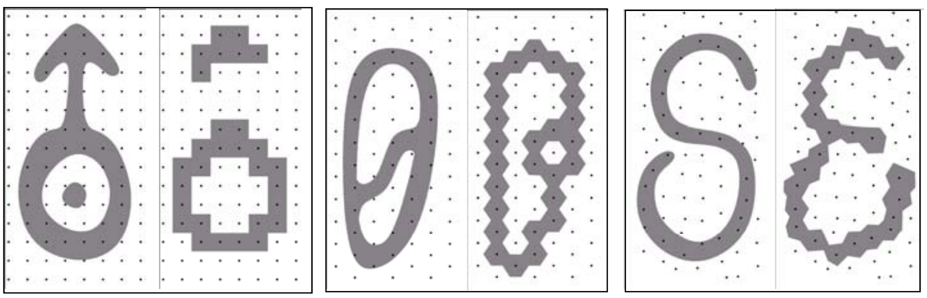
Sampling of Binary Images (1)

Problem: Shapes may change under digitization



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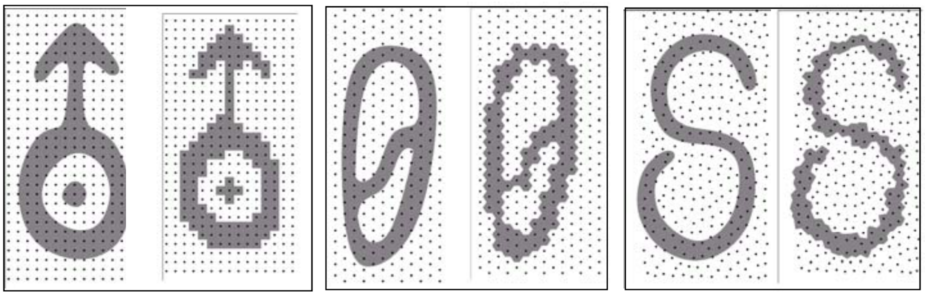
Sampling of Binary Images (2)

Problem: Shapes may change under digitization



This cannot be solved by using Shannon´s Theorem since binary images are not bandlimited.

Shape Preserving Sampling Theorem (1)

Shape Preserving Sampling Theorem:
The shape of an r-regular image can be correctly reconstructed after sampling with any sampling grid, if the grid point distance is not larger than r.

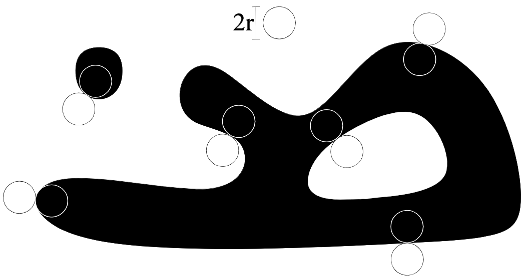
Stelldinger, Köthe 2003

"grid point distance": maximal distance from arbitrary sampling point to the next sampling point

"r-regular binary image":

osculating r-discs at each boundary point of the shape

⇒ curvature bounded by 1/r
⇒ bounded thinness of parts
⇒ minimal distance between parts



Shape Preserving Sampling Theorem (2)

What does correct reconstruction mean?

Topological and geometric similarity criterion:

One shape can be mapped onto the other by twisting the whole plane, such that the displacement of each point is smaller than r.

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Sampling of Shapes in Arbitrary Images (1)

The previous sampling theorem also holds for greyvalue images, if each level set is an r-regular shape.

A "level set" is the set where the image is brighter than a given threshold value.

sampling + reconstruction

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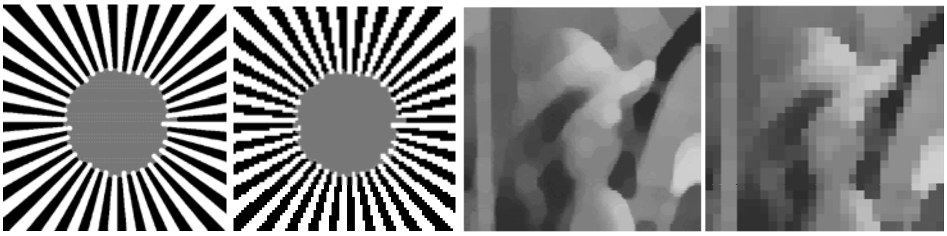
Sampling of Shapes in Arbitrary Images (2)

Reconstruction after sampling from r-regular originals



There exist generalizations to more complex cases (e.g. higher dimensions, blurring, colors, noise).

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Comparison of the Sampling Theorems

	Shannon´s Sampling Theorem	Shape Preserving Sampling Theorem
necessary image property	bandlimited with bandwidth W	r-regular
equation	$\left(\frac{r'}{\sqrt{2}} =\right) d < \frac{1}{2W}$	$r' < r$
reconstructed image	identical to original image	same shape as the original image
prefiltering	band-limitation: efficient algorithms (but shapes may change!)	regularization: unsolved problem
2D sampling grid	rectangular grid	arbitrary grids
dimension of definition	1D (generalizable to n-D)	2D (partly generalizable to n-D)

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Quantization of Greyvalues

Quantization of greyvalues transforms continuous values of a sampled image function into digital quantities.

Typically 2 ... 2^{10} quantization levels are used, depending on task.

Less than 2^9 quantization levels may cause artificial contours for human perception.

<u>Example</u>:

256 16 8 4 2

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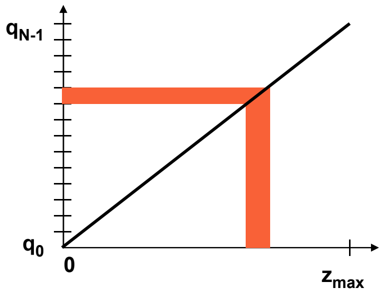
Uniform Quantization

Equally spaced discrete values $q_0 \dots q_{N-1}$ represent equal-width greyvalue intervals of the continuous signal.

Typically $N = 2^K$ for K = 1 ... 10



Uniform quantization may "waste" quantization levels, if greyvalues are not equally distributed.

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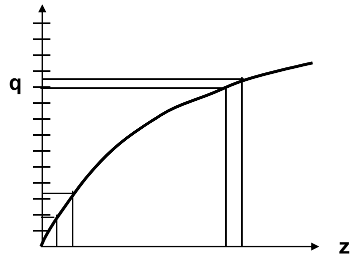
Nonlinear Quantization Curves

E.g. fine resolution for "interesting" greyvalue ranges, coarse resolution for less interesting greyvalue ranges.

<u>Example</u>:
Low greyvalues are mapped into more quantization levels than high greyvalues.



<u>Note</u>:

Subjective brightness in human perception depends (roughly) logarithmically on the actual (measurable) brightness.

To let the computer see brightness as humans, use a logarithmic quantization curve.

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Optimal Quantization (1)

<u>Assumption</u>:

Probability density p(z) for continuous greyvalues and number of quantization levels N are known.

<u>Goal</u>:

Minimize mean quadratic quantization error d_q by choosing optimal interval boundaries z_n and optimal discrete representatives q_n.

$$d_q^2 = \sum_{n=0}^{N-1} \int_{z_n}^{z_{n+1}} (z - q_n)^2 p(z) dz$$

Minimizing by setting the derivatives zero:

$$\frac{\delta}{\delta z_n} d_q^2 = (z_n - q_{n-1})^2 p(z_n) - (z_n - q_n)^2 p(z_n) = 0 \quad \text{for } n = 1 \ldots N-1$$

$$\frac{\delta}{\delta q_n} d_q^2 = -2 \int_{z_n}^{z_{n+1}} (z - q_n) p(z) dz = 0 \quad \text{for } n = 0 \ldots N-1$$

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Optimal Quantization (2)

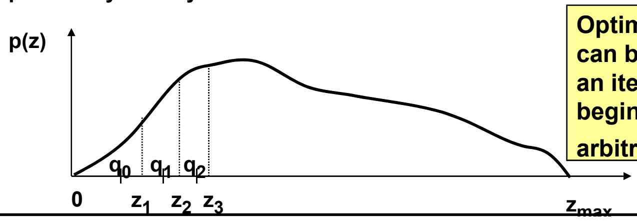
Solution for optimal quantization:

$$z_n = \frac{1}{2}(q_{n-1} + q_n) \quad \text{for } n = 1 \ldots N-1 \text{ when } p(z_n) > 0$$

Each interval boundary must be in the middle of the corresponding quantization levels.

$$q_n = \frac{\int_{z_n}^{z_{n+1}} z\,p(z)\,dz}{\int_{z_n}^{z_{n+1}} p(z)\,dz} \quad \text{for } n = 0 \ \ldots \ N-1$$

Each quantization level is the center-of-gravity coordinate of the corresponding probability density area.



Optimal quantization can be determined by an iterative algorithm beginning with an arbitrary choice of z_1

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Binarization

For many applications it is convenient to distinguish only between 2 greyvalues, "black" and "white", or "1" and "0".

<u>Example</u>: Separate object from background

Binarization = transforming an image function into a binary image

<u>Thresholding</u>:

$$g(x, y) \Rightarrow \begin{cases} 0 & \text{if } g(x, y) < T \\ 1 & \text{if } g(x, y) \geq T \end{cases}$$

T is threshold

Thresholding is often applied to digital images in order to isolate parts of the image, e.g. edge areas.

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Threshold Selection by Trial and Error

A threshold which perfectly isolates an image component must not always exist.

Selection by trial and error:

Select threshold until some image property is fulfilled, e.g.

$$q = \frac{\#\ \text{white pixels}}{\#\ \text{black pixels}} \Rightarrow q_0$$

line strength $\Rightarrow d_0$

number of connected components $\Rightarrow n_0$

Number of trials may be small if logarithmic search can be used.

Example:

At most 8 trials are needed to select a threshold $0 \leq T \leq 255$ which best approximates a given q_0.

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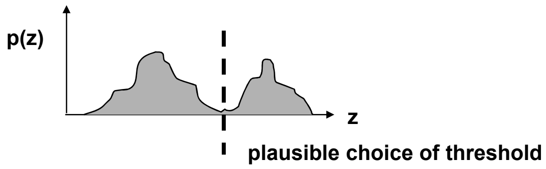
Distribution-based Threshold Selection

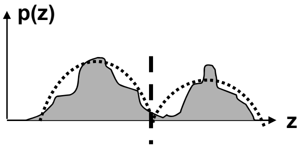
The greyvalue distribution of the image function may show a bimodality:



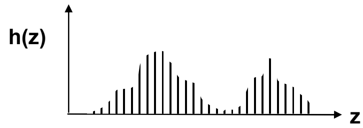
Two methods for finding a plausible threshold:

1. Find "valley" between two "hills"

2. Fit hill templates and compute intersection



Typically, computations are based on histograms which provide a discrete approximation of a distribution.



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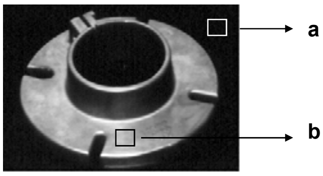
Threshold Selection Based on Reference Positions

In many applicatons, the approximate position of image components is known a priori. These positions may provide useful reference greyvalues.

<u>Example</u>:



possible choice of threshold:

$$T = \frac{a+b}{2}$$

Threshold selection and binarization may be decisively facilitated by a good choice of illumination and image capturing techniques.

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Image Capturing for Thresholding

If the image capturing process can be controlled, thresholding can be facilitated by a suitable choice of

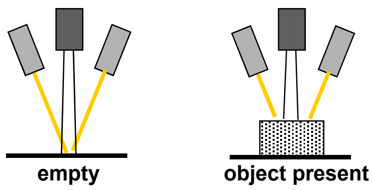
- illumination
- camera position
- object placement
- background greyvalue or colour
- preprocessing

<u>Example</u>: Backlighting

Illumination from the rear gives bright background and shadowed object

<u>Example</u>: Slit illumination

On a conveyor belt illuminated by a light slit at an angle, elevations give rise to displacements which can be recognized by a camera.



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