# Liste der noch zu erledigenden Punkte

# Kapitel 1

# 1.Overview

- „image society“ (webpages: 1995 text-based, 2005 image based, 2015 video based . . . )

  - data transfer rates ↑, compression rates ↑

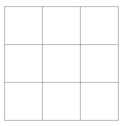
  critical shift: reading → watching

- „Photoshop“-ing (remove wrinkles, bumps, . . . )

- Images in medicine („medical image proscessing“), x-ray, CT, MRI, ultrasound, . . . („modalities“).
  different questions:

  1.) Layout!

  align bottom measurments $\overset{?}{\Rightarrow}$ image
  expl: tomography
  ⇒ difficult mathematical problems

  2.) Image enhancements

  – denoising
    simple pixels/lines: „sandpaper“ interpolation
    global noise: smoothing

  so richtig?

  – grayscale
    histogramm balancing (spreading)

  – distortion
    makes straight lines (in real world) straight (in the images)

  – edge detection
    contour enhancement

  – segmentation
    detect and separate parts of the image

  – registration
    *sequence* of images of the same object ⇒ Wort? , compare Skizze
    ↗ object following in a movie

**<u>Our Focus:</u>**

- mathematical models/methods/ideas
- (algorthms)
- ((implementation))

skipped: Very fast intro: Matlab and images

# Kapitel 2

# 2.What is an image?

## 2.1 Discrete and continuous images

There are (at least) two different points of view:

**Discrete / Digital**

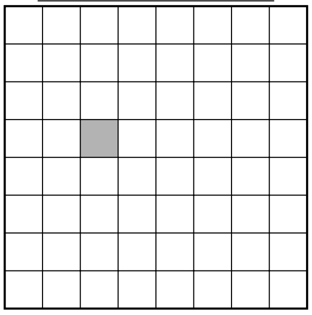


Abbildung 2.1: Discrete Image

**Continous / Analogue**

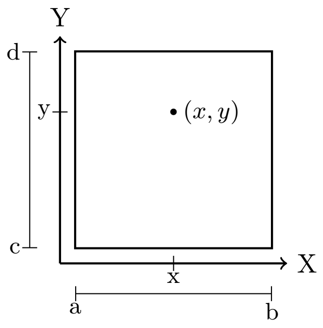


Abbildung 2.2: Continous Image

| | | |
|---|---|---|
| **object:** | matrix | function |
| **tools:** | linear algebra (SVD, . . . ) | analysis (differentrage, integrate, . . . ) |
| **pros:** | (finite storage) storage, complexity | freedom, tools, motions?P.4 (e.g. edge discontinuity) |
| **cons:** | limitations: zooming, rotations, . . . | storage (infinite amout of data) |

arguably, one has:

- real life ⇒ continuous „images“ (objects)
- digital camers ⇒ discrete images

In general we will say:

**Definition 2.1** ((mathematical) image)**.** A (mathematical) *image* is a function

$$u : \Omega \to F,$$

where: $\Omega \subset \mathbb{Z}^d$ (discrete) or $\Omega \subset \mathbb{R}^d$ (continuous) . . . *domain*
$d = 2$ (typical case 2D), $d = 3$ („3D image“ = body or $\underbrace{\text{2D + time}}_{\text{movie}}$)

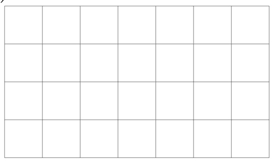
$d = 4$ (3D + time)

$F$ ... *range of colours*

$F = \mathbb{R}$ or $[0, \infty]$ or $[0, 1]$ or $\{0, \dots 255\}$, ... grayscale (light intensity)

$F \subset \mathbb{R}^3$ ... RGB image (colored)

$F = \{0, 1\}$ ... black/white



3 Layers
$\Rightarrow$ colored images:w

Matlab stuff

Large parts of the course: analytical approach (i.e. continuous domain $\Omega$)
Since we want to differentirate, ... the image $u$.

Still: need to assume that also $F$ ist continuous (not as $\{0, 1\}$, $\{0, 1, \dots, 255\}$ or $\mathbb{N}$) since otherwise the only differentiable (actually, the only continuous) functions $u : \Omega \to F$ are *constant* functions $\Leftrightarrow$ single-colour images

Also: We usually take $F$ one-dimensional ($F \subset \mathbb{R}$). Think of it as either

- gray scaled image, or
- treating R,G & B layer separately

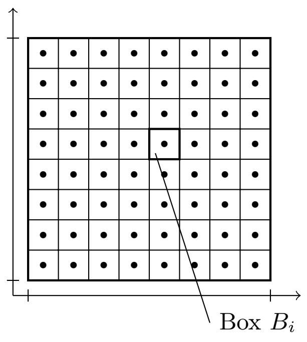
## 2.2 Switching between discrete and continuous images

### continuous $\to$ discrete:

- divide the continuous image in small squared pieces (boxes) (superimpose grid)
- now: represent each box by *one* value
  - strategy 1: take function value $u(x_i)$ for $x_i$ = midpoint of box $B_i$
  - strategy 2: use mean value

$$\frac{1}{|B_i|} \int_{B_i} u(x)dx$$

$\Omega =$



$\Rightarrow$ discrete image

strategy 1: simple (and quick) but problemativc ($u(x_i)$ might represent $u|_{B_i}$ badly; for $u \in L^p$, single point evaluation not even defined)

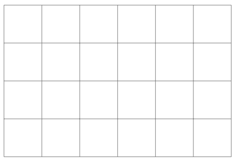
strategy 2: more complex but also more „democratic" (actually closer to the way how CCD Sensors in digital camers work)

often the image value of the box $B_i$ gets also digitized, i.e. fitted (by scaling & rounding) into range $\{0, 1, dots, 255\}$

### discrete $\to$ continous

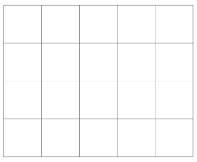
This is of course more tricky ...

- Again: each pixel of the discrete image corresponds to a „box" of the continuous image (that is still to be constructed)
- Usually: pixel value $\mapsto$ function value at the *midpoint* of the box
- Question: How to get the other function values (in the box)?



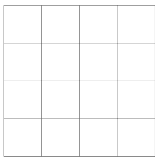
idea 1: just take the function value of the nearest midpoint („nearest neighbour interpolation")

For each $x \in B_i : u(x) := u(x_j)$ where $|x - x_j| = \min_k |x - x_k|$



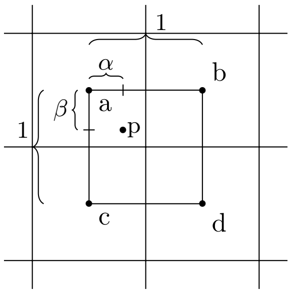
$\Rightarrow$ $u(x) = u(x_i)$ for all $x \in B_i$
$\Rightarrow$ each box is uni-color
$\Rightarrow$ the continuous image is essentially still discrete

idea 2: (bi-) lineare interpolation



Let $a, b, c, d \ldots$ function values at 4 surrounding adjacent midpoints ($\nearrow$ figure)
$\alpha, \beta, 1-\alpha, 1-\beta \ldots$ distance to dotted lines ($\nearrow$ figure, w.l.o.g, bob is $1 \times 1$)

interpolation (linear) on the dotted line between $a$ and $b$:



$e := a + \alpha(b - a) = (1 - \alpha)a + \alpha b$
(1D - interpolation, convex combination)

Similarly: $f = (1 - \alpha)c + \alpha d$

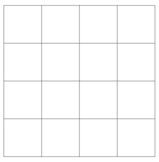
Then: The same 1D-interpolation between $e$ and $f$

$$\begin{aligned} \Rightarrow u(x) :&= (1-\beta)\cdot e + \beta \cdot f \\ &= (1-\beta)[(1-\alpha)a + \alpha b] + \beta[(1-\alpha)c + \alpha d] \\ &= \underbrace{(1-\alpha)(1-\beta)}\, a + \underbrace{\alpha(1-\beta)}\, b + \underbrace{(1-\alpha)\beta}\, c + \underbrace{\alpha\beta}\, d \end{aligned}$$

$\in [0,1] \wedge \sum = 1$

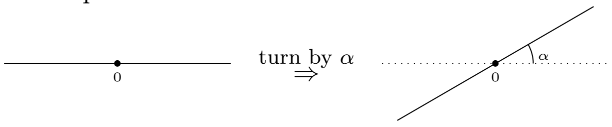
$\Rightarrow$ convex combination of the function values $a, b, c, d$ at the the surrounding 4 midpoints (on which points is the nearest instead of taking just $a, b, c$ or $d$ - depending)
$\Rightarrow$ 2D linear interpolation, *bi-linear interpolation* (can be interpreted as spline interpolation with bilinear basis splines).

**Beispiel 2.2.** Rotate image



by angle $\phi \neq k \cdot \frac{\pi}{2}$

- continuous image case: no problem



$$x = D_\varphi\, y \qquad x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix},\ y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix},\ D_\varphi = \begin{pmatrix} \cos\varphi & -\sin\varphi \\ \sin\varphi & \cos\varphi \end{pmatrix}$$

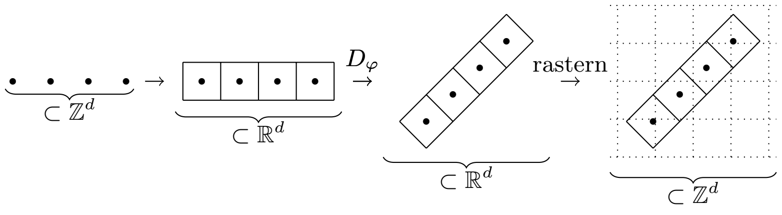
2D rotation matrix

$$y = D_\varphi^{-1}\, x = D_{-\varphi}\, x$$

$\Rightarrow v(x) := u(y) = u(D_{-\varphi}\, x) \quad \forall x \in$ domain of the rotated image

- discrete image case: problem !

  For $x \in$ domain of notated image, in general $D_{-\varphi}\, x \notin$ domain of original image[1]
  Way out: $v(x) :=$ *interpolation* between the $u(\cdot)$ of the 4 surrounding pixels of $D_{-\varphi}$



Something to think about:
What happens in the limit (?) if we, starting with an image (discrete or continuous), repeatedly switch between discrete and continuous, non-stop . . . ?
Does the answer depend on the way of switching ? (continuous $\rightarrow$ discrete: midpoint or average, discrete $\rightarrow$ continuous: nearest neighbour or bilinear?)

[1] it's not an integer

# Kapitel 3

# 3.Histogramm and first applicatsion

## 3.1 The histogramm

**Definition 3.1** (histogram)**.** Let $\Omega \subset \mathbb{Z}^d$, $F \subset \mathbb{R}$ discrete and $u : \Omega \to F$ a discrete discrete image. The function

$$H_u : F \to \mathbb{N}_0 \ (:= \mathbb{N} \cup \{0\})$$

with

$$H_u(k) := \# \{x \in \Omega : u(x) = k\}, \quad k \in F$$

is called *histogramm* of the image $u$.

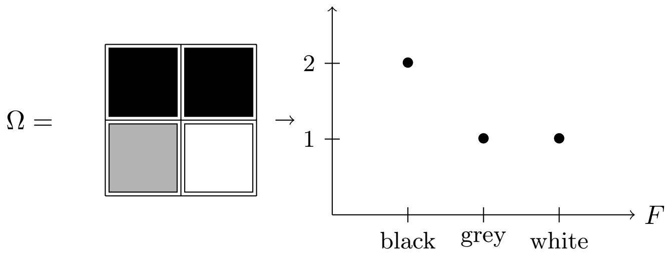
$H_u(k)$ counts how often colour $k$ appears in $u$.

$$\sum_{k \in F} H_u(k) = |\Omega| = \text{number of pixels in the whole image}$$

or

$$\frac{H_u(k)}{|\Omega|} \begin{array}{l} = \text{relative frequence of colour } k \text{ in image } u \\ \text{(relative Häufigkeit)} \end{array}$$

**Beispiel 3.2.**



If $u$ ist a continous image, $H_u$ can be understood as measure (generalized function)[1]. Another way to writ this:

$$H_u(k) = \sum_{x \in \Omega} \delta_{u(x)}(k), \ k \in F \qquad H_u(k) = \int_\Omega \delta_{u(x)}(k) dx, \ k \in F$$

hier fehlt noch das Kronecker underarrow

Matlab-Code

[1]density of a probability distribution

## 3.2 Application: contrast enhancement

If the image only uses a small part of the available colour/grayscale „palette“ $F$, then its contrast can be improved by „spreading“ the histogramm over all of $F$.

Simple idea:

$$v = \varphi \circ u$$
$$v(k) = \varphi(u(k))$$

The above simple idea („contrast stretching“) corresponds to

$$\begin{aligned} \varphi : & \; k_{\min} \mapsto 0 \\ & \; k_{\max} \mapsto N \\ & \; \text{and linear in between} \\ \text{i.e} \qquad \varphi(k) &= \left[ \frac{k - k_{\min}}{k_{\max} - k_{\min}} \right] \end{aligned}$$

Where $[\;\cdot\;]$ means . . . rounding to the nearest integer (assumuning that $F = \{0, 1, \dots, N\}$.

A bit more sophisticated:

$$\begin{aligned} \varphi : \; & (k_{\min} \mapsto 0) \\ & k_{\max} \mapsto N \\ & \text{and } \textbf{non} \text{ linear in between} \end{aligned}$$

such that colour ranges that occur more frequently in $u$ can occupy a larger range of colours in $u$. ($\Rightarrow$ visibility $\uparrow$)

Example histogramm:

spread out according to frequency of occurence:

$\Rightarrow$ „density“ is equalized over $F = \{0, \dots, N\}$

Ideal would be:

Layout S.12 u

Note: The new colours (i.e the location of the bars in the histogramm of $u$) only depend on the frequencies / *height* of the bars in $H_u$ but not on the colours/location of the bars in $H_u$

Finally: The formula

$$\varphi(k) = \left[ \frac{N}{|\Omega|} \sum_{l=0}^{k} H_u(l) \right]$$

This process is called „histogramm equalization“

Exercise ?!

## 3.3 Another application: conversion to b/w

Task: convert grayscale image to black white
- interesting for object detection/*segmentation* ...!

Idea: Find a threshold $t \in T$ s.t. the histogramm splits into two „characteristic“ parts

For $t \in F$ put

$$\begin{aligned} \text{black} &:= \{k \in F : k \leq t\} \\ \text{white} &:= \{k \in F : k > t\} \end{aligned}$$

and

$$\tilde{u} := \begin{cases} 0, & u(x) \in \text{black} \\ 1, & u(x) \in \text{white} \end{cases} \qquad \tilde{F} = \{0, 1\}$$

How to find the threshold $t$:

1.) Shape based methods
If the histogramm is „biomodal“
Put $t := \dfrac{k_{\max_1} + k_{\max_2}}{2}$
or $t := k_{\min}$