Interpretation of visual and range data for robotics – 3d maps and color

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Robots must prove their skills for autonomous exploration of the environment in several leagues in RoboCup. In the @home-league the environment is made like a living room; in the rescue-league the robots search for victims in collapsed buildings. Both challenges will be introduced shortly to motivate the technological problems that will be detailed in the following.
The exploration of an unknown environment is possible by sensors that capture data from varying positions. This results in a map where the robot marks its own position. As location and environment are unknown, this sounds like a egg-hen problem known as SLAM. For the 2d case this is considered to be solved. For 3d sensors and maps this is subject of current research. Several measurement systems are commercially available. We show their principles and possible use by examples. We also show our own solution.

In both scenarios, objects need to be found. This task is mostly accomplished by fusion of 3d data and color images. The task of object recognition and it's underlying algorithmic problem, namely image segmentation, is not completely solved yet, although it has been investigated for many years. We present recent work of color image segmentation.

Dietrich Paulus

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- active vision — Paulus (2001)
- medical image processing — Münzenmayer et al. (2006)
- model-based image analysis — Paulus et al. (1993)
- color vision — Gossow et al. (2010)
- 3d reconstruction — Decker et al. (2008)
- robotics — Nüchter et al. (2009)


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Rolandseck
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Ockenfels
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Dattenberg
Schloss Arenthal (Sinziger Schloss)
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Rhein
Altwied
Rheineck
Hammerstein
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HESSEN
RHEINLAND-
PFALZ
Mosel
Welterbe
Kulturlandschaft
Oberes Mittelrheintal
Schloss
Festung
Burg/Fort
Ruine
0
20 km

Computational Visualitics Koblenz

COMPUTERVISUALISTIK

- Magdeburg
- Koblenz

A certain brand name

- interdisciplinary curriculum (80% comp. sc., 20% arts, etc.)
- visual equivalent to computational linguistics
- focus on graphics and vision, modeling, and linguistics
- 650 students (35% female)
- +500 in comp. science

Bachelor programs for

- Computer Science
- Computational Visualistics
- Information Management

Master programs for

- Computer Science
- Computational Visualistics
- Information Management
- Information Systems

Strong influence of army in Koblenz:

- Important military garnison
- Military clinics
- several other clinics


Outline

3D Maps

- Scientific work
- Results from robotics
- own results
- comparison to other results
- market
- own system

Color Segmentation

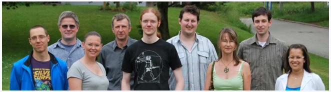
- Scientific work
- results from joint work in Poitiers with Noël Richard and Mihai Ivanovici

Robotics $\rightarrow$ Sensors (Color / Segmentation) $\rightarrow$ Maps (Objects) $\rightarrow$ Rooms

algorithms, problems, solutions, techniques

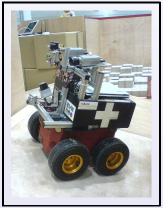
Arbeitsgruppe Aktives Sehen

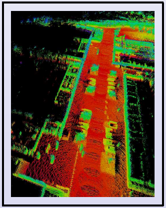
Prof. Dietrich Paulus

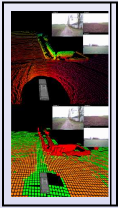


Robotik

- Autonomous robots
- mapping using laser sensors
- sensor fusion
- SICK Robot Day
- RoboCup Rescue
- **RoboCup@Home**







Why robots in household?

3 D's of robotics

Dull

Dirty

Dangerous

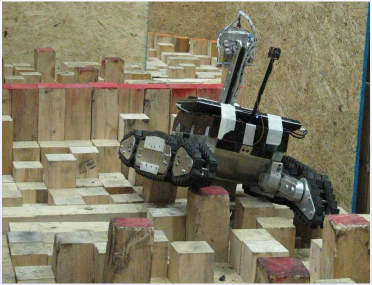
Challenges

Technology is pushed by challenges (cmp. postal address database)

- RoboCup Rescue (following disasters in Kobe)
- RoboCup @home
- Grand Challenge

- Technological transfer, also mobile devices

RoboCup Rescue



RoboCup Rescue Arena 2007; Roboter Team Resquake

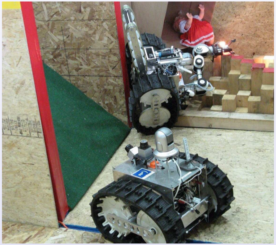
- Robot league
- Simulation league (Virtual Robots - USAR Sim)
- Simulation league (Agent Simulation)

RoboCupRescue: Arena /1

Task: **Find victims and map the disaster site (20 min)**
Arena size: about 20 m $\times$ 20 m

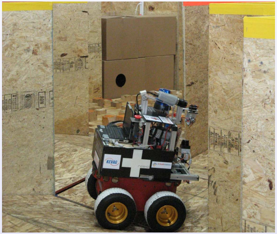
RoboCupRescue: Arena /2

Orange/Red Arena



- for remote controlled robots
- stepfields, stairs, steep ramps
- focus on mobility, HRI

Yellow Arena



- for autonomous robots
- random maze, ramps (10^o)
- focus on autonomy (victim detection, SLAM)

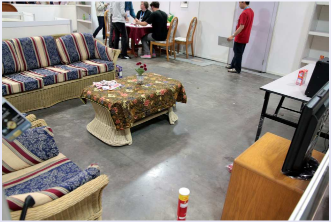
Arena developed and built by NIST (U.S. National Institute of Standards and Technology)

RoboCup@Home

(Quelle: Robbie X)

- Different tasks in houshold
- Mobile manipulation: "‘Bring me some juice"’
- Follow me
- Learn and recognize locations

Arena 1



- Scenario
  - changed each year
  - more and more complex
  - realistic and typical for the country where the challenge takes place
  - Home, office, garden...
  - 2010: Shopping Mall

Go Get It!

Robot needs to find objects and return them to start position

- 2 2 robots at the same time
- Give them one order and one hint
- Challenges
  - HMI (natural language)
  - reliable naviagation
  - Object recognition
  - Object manipulation

Videos on LISA and Robbie can be found in

`robots.uni-koblenz.de`

DARPA Challenges / Autonomous Cars

Grand Challenge
2004/2005: Desert

Stanley
Stanford
Drives through
Desert

Urban Challenge
2007: City

Winner: Boss
Tartan Racing,
CMU

CarLO

Leonie, TU
Braunschweig.
Drives through
Braunschweig
(real-life)

. . . more to come in near future (driving assistance, autonomous trucks, . . .)

Sources:
`http://cs.stanford.edu/group/roadrunner//old/announcements.html`
`http://www.ifr.ing.tu-bs.de/forschung/stadtpilot/stadtpilot.php`

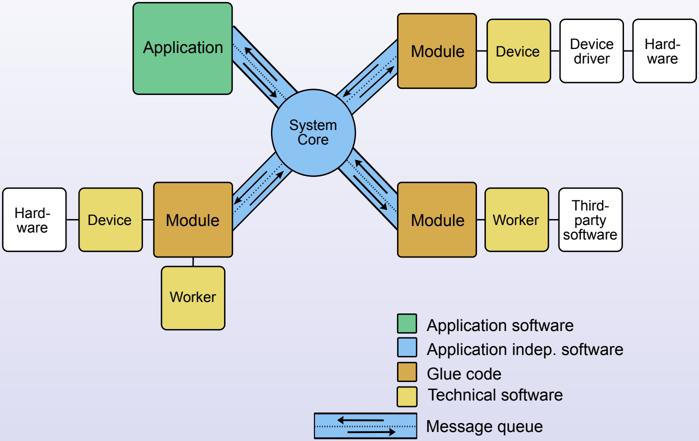
Problem Statement

Autonomous robots

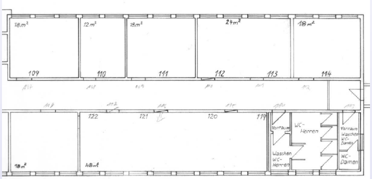
- Knowledge on environment
- Path planning
- Exploration
- Object recognition (obstacles, tools, objects, humans, ...)
- Self localization

Result: maps of *environment (including objects)*
Method: SLAM

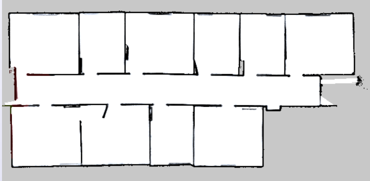
Software Architecture @ AGAS



Representation 2D



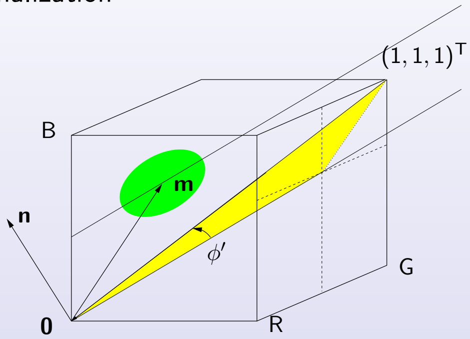
map of building



computed automatically

Illumination change

Problem: Recording of object and scene with different illuminations
Solution: Normalization



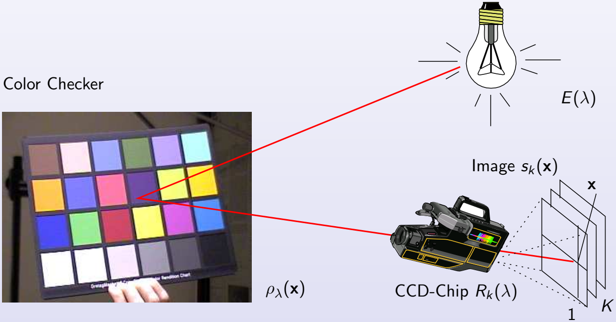
1. Intensiy normalization
2. CCN Finlayson et al. (1998), (extended in Csink et al. (1998))
3. PCA (followed by rotation Csink et al. (1998))

Color Cameras


RGB Rotation Gray-world assumption




Linear radiometric calibration



Discrete Device Sensitivity

According to Alsam and Finlayson (2002): a sum of $L = 31$ samples

$$s_k(\mathbf{x}) = \sum_{\lambda=1}^{L} E_\lambda \cdot \rho_\lambda(\mathbf{x}) \cdot R_{k,\lambda} \cdot \Delta\lambda \quad . \tag{1}$$

Vector $\mathbf{E} = [E_\lambda]_{\lambda=1\ldots L}$: spectral energy distribution for light,
Vector $\boldsymbol{\rho}(\mathbf{x}) = [\rho_\lambda(\mathbf{x})]_{\lambda=1\ldots L}$: discrete reflectance at position $\mathbf{x}$
Matrix $\mathbf{R} = [R_{k,\lambda}]_{k=1,\ldots,K,\lambda=1\ldots L}$ sensitivity curves of the sensors

Result in Paulus et al. (2002)

Using SVD, regularization, smoothing, rank constraints, further constraints:

$$\mathbf{r} = \left(\mathbf{VP\Sigma}^2\mathbf{V}^\mathsf{T} + \mu \cdot \mathbf{G}\right)^{-1} \mathbf{VP\Sigma U}^\mathsf{T}\mathbf{s} \quad . \tag{2}$$

Distance Measuring

Goal: 3D / Distance Measurements
Methode

- 3D camera
  (TOF, Laser, ...)
- 2D cameras + geometric considerations
  (Stereo, ...)

Hokuyo URG-04LX

Fig.: URG-04LX

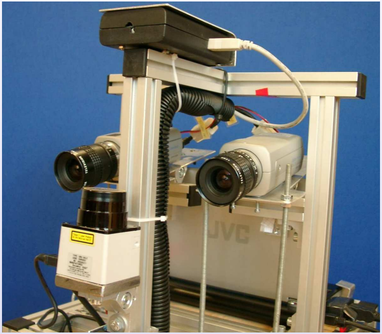


Fig.: mounted scanner

Hokuyo URG-04LX

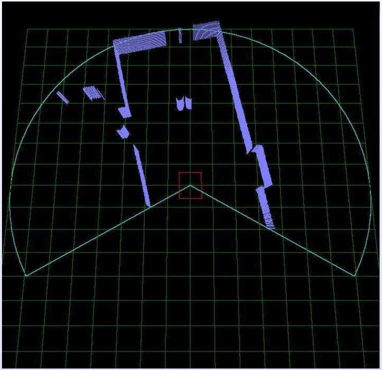


Fig.: Laser scan

Techical data

- *scanning range:* 240°, 20 - 4000 mm
- *resolution:* 682 Punkte (0,352°)
- *distance resolution:* 1 mm
- *error:* max. 1%
- *scan time:* 100 ms

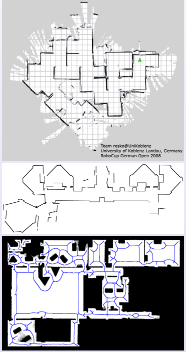
Sensor fusion

- Image
- Laser
- GPS
- Odometry
- Inertial sensor

Kalman Filter

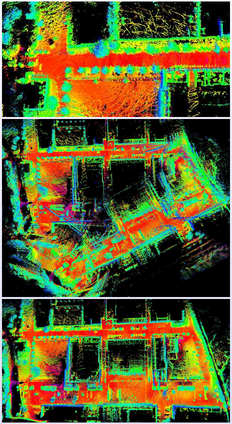
Representations for maps

- 2D maps
  - Occupancy Grid Maps
  - Feature maps
  - Topological maps
  - Semantic maps (including annotations, objects, ...

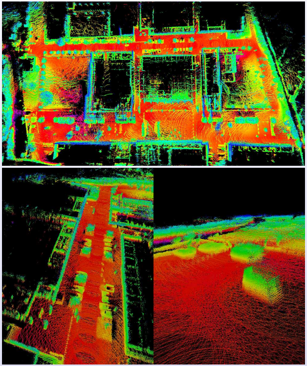


Map correctness

- locally consistent maps
- globally consistent maps
- globally correct maps

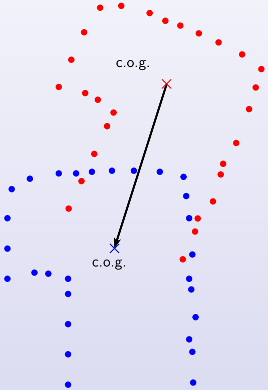


Local Maps



ICP-algorithm

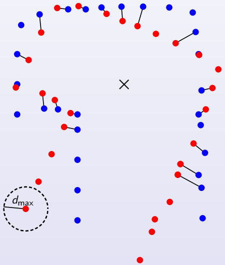
- model M
- data D
- center of gravity $(\mathbf{c}_m, \mathbf{c}_d)$
- register $\mathbf{m'}_i, \mathbf{d'}_i$



ICP-algorithm

- find corresponcences
- limit d_{max}
- minimize error function:

$$E(\mathbf{R},\mathbf{t}) = \sum_i \|\mathbf{m}'_i - (\mathbf{R}\mathbf{d}'_i + \mathbf{t})\|^2$$



repeat until

- below threshold
- reached maximum number of iterations

Minimization of ICP function

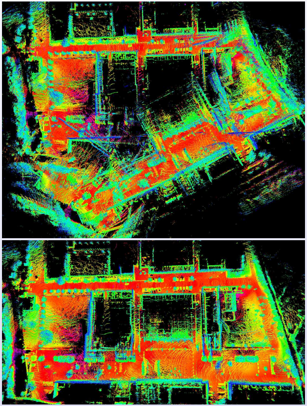
Estimation of transformation by

- SVD
- Quaterninons
- Dual quaternions
- Helix transformation — Nüchter et al. (2010)

Comparison: (Lorusso et al. 1995)

- SVD is best
- Dual quaternions: good for large data sets

Global Maps



The SLAM problem

Simultaneous Localization and Mapping

Goal

Find most probable map and most probable robot location using previously recorded sensor information.

maximize

$$p(x_{1:t}, m | z_{1:t})$$

- $x_{1:t}$: robot path (positions x_1 to x_t)
- m: map
- $z_{1:t}$: sensor data

SLAM for Robbie-6

Incremental Mapping

Simplification

- only **one** map
- position depends on previous estimate plus motion

$$p(x_t | x_{t-1}, z_t, m)$$

- x_t: current location
- x_{t-1}: previous location
- z_t: current sensor data (laser and odometry)
- m: map

Most probable position is used to extend map.

Motion model

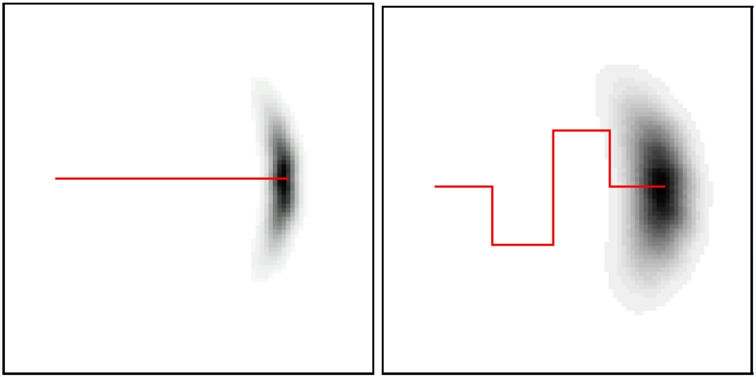


Fig.: Location densities after move of robot

Particle filter

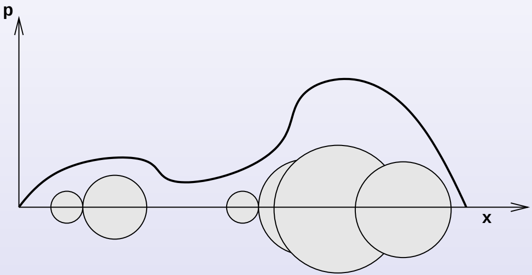
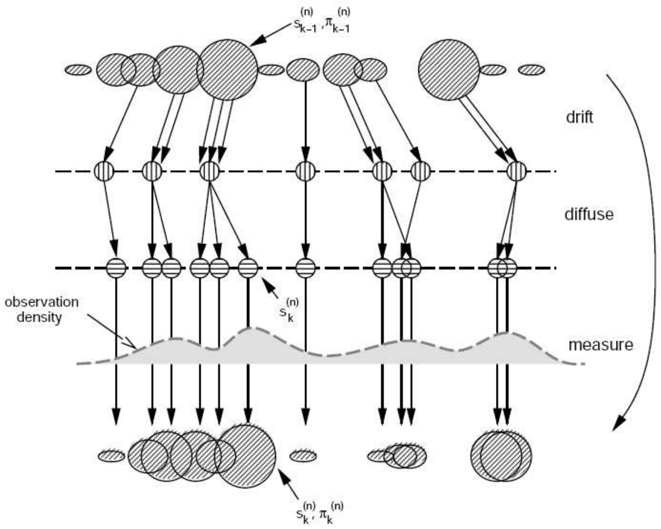


Fig.: Location density

Particle = state + weight

$$P = (X, \pi)$$

Condensation algorithm



Measurement step

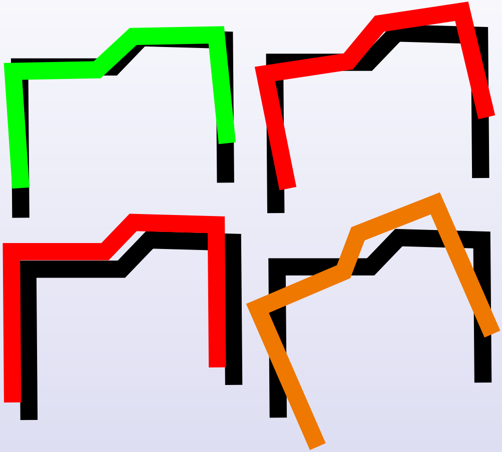
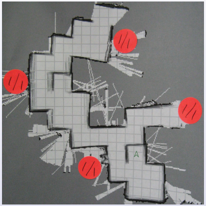
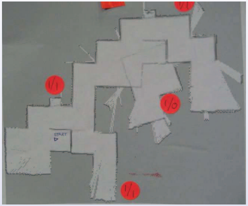


Fig.: Examples for weights of measures

Problems in maps: Visible without ground truth!



Map with blurry "shadow walls"



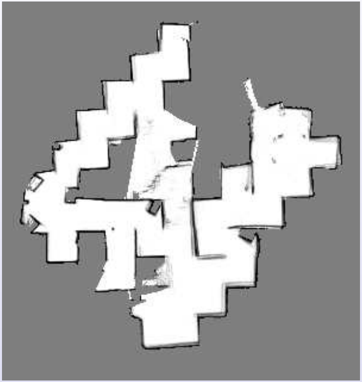
Map with broken part

Ideas:

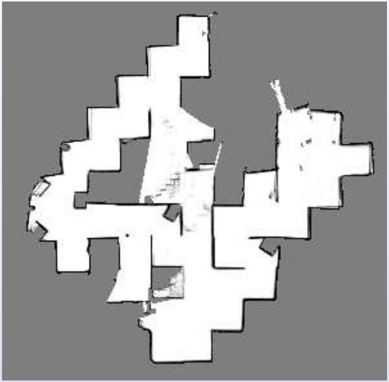
1. Analyze **contrast** of the map ($\triangleright$ ρ_1)
2. Analyze **directions** of the walls ($\triangleright$ ρ_2)

Idea see Pellenz and Paulus (2009)

ρ_1: Sharpness of a map example



Map $\mathbf{m}_1$ generated using 50 particles: Contrast ρ_1 $(\mathbf{m}_1) =$ **87.4**



Map $\mathbf{m}_2$ generated using 1000 particles: Contrast ρ_1 $(\mathbf{m}_2) =$ **92.6**

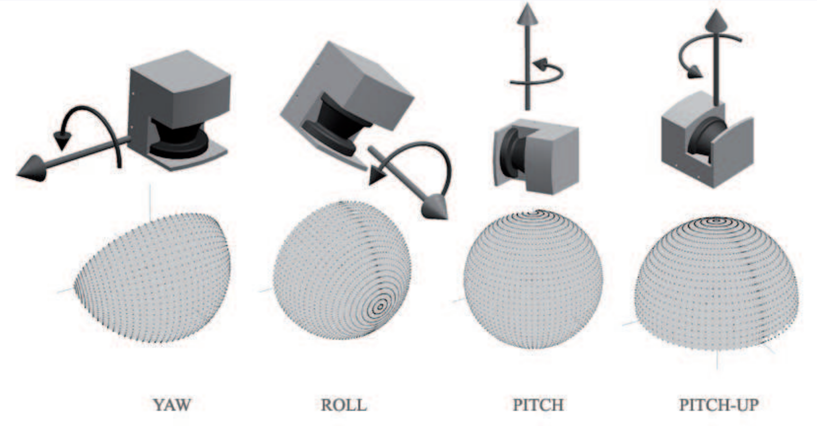
Hyper-Partikelfilter

Idea: **Use a particle filter of localization particle filters!**

- **Localization Particle Filter (LPF)**:
  Particles $\boldsymbol{\pi}_i = \langle \mathbf{x}^{[i]}, w\mathbf{x}^{[i]} \rangle$, with $\mathbf{x}^{[i]} = (x^{[i]}, y^{[i]}, \theta^{[i]})$.
- **Hyper Particle Filter (HPF)**:
  Particles $\mathbf{q}_j = \langle \mathbf{y}^{[j]}, w\mathbf{y}^{[j]} \rangle$ with $\mathbf{y}^{[j]} = (lpf^{[j]}, \mathbf{m}^{[j]})$
  where $lpf^{[j]}$ is a particle filter of type LPF and $\mathbf{m}^{[j]}$ the corresponding map.
- The weight $w\mathbf{y}^{[i]}$ is determined by the map quality measures.

Measurement principle of 3D-Laser Range Finder

Move scan device:



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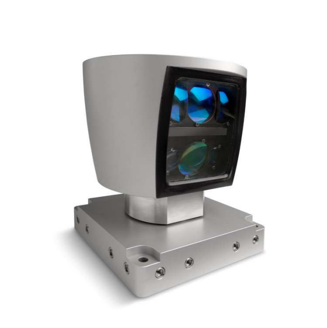
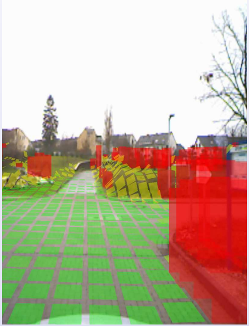
[1] Poppinga et al. (2009)

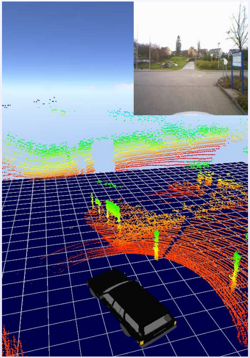
Velodyne I

Grand Challenge

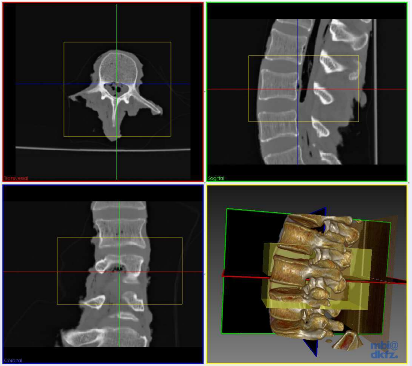


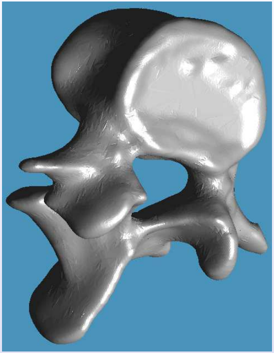
Velodyne II





Volumes and surfaces





3D

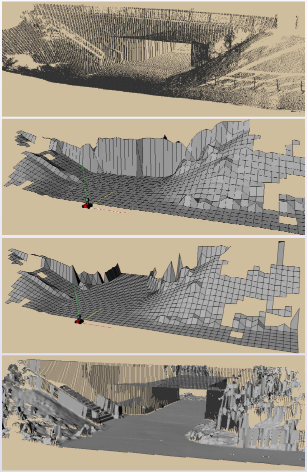
2.5 D

Dimension

We should call it 2.5 d

3D map types

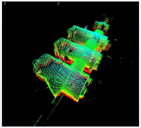
- $2\frac{1}{2}$D maps
  - elevation mapps
  - extended elevation maps
  - multi-surface maps

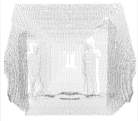


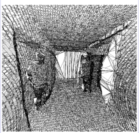
(Source: Pfaff et al. (2007))

3D map types

- 3D maps
  - 3D point clouds
  - 3D octal trees
  - 3D triangulated meshs



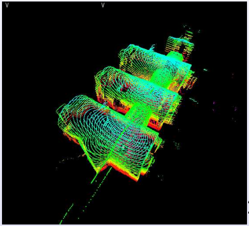




(source: own MappingCube) (source: Nüchter et al. (2007)) (source: Nüchter et al. (2007), Pfaff et al. (2007))

Represenation 3D

point cloud



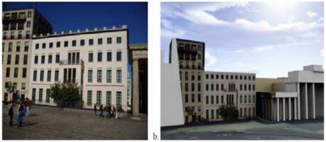
[2]

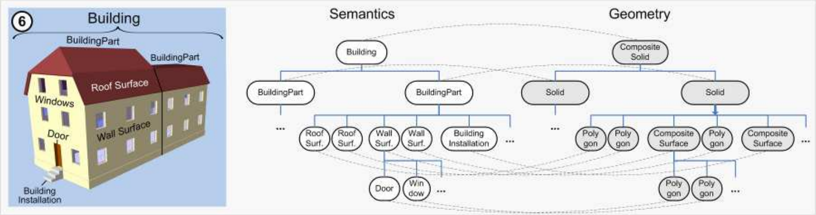
CityGML Groeger et al. (2008)

[3]

[2]Fort Konstantin, Koblenz, recorded with V&R MappingCube
[3]From http://www.citygml.org/fileadmin/citygml/docs/CityGML_FME2009.pdf

3D Maps

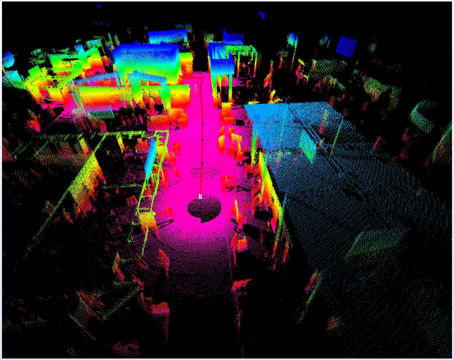




3 all images from http://www.citygml.org/fileadmin/citygml/docs/CityGML_FME2009.pdf

MappingCube 3D V&R Vision & Robotics I

MappingCube 3D

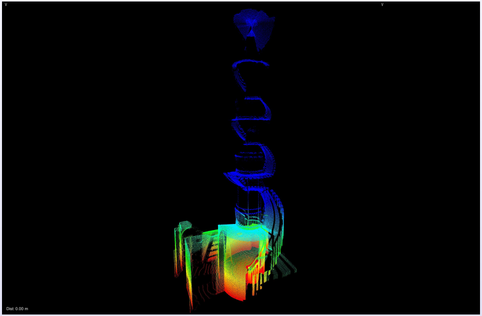


3D Scan at Control 2010

MappingCube 3D V&R Vision & Robotics I

Properties:

- online registration of scans
- all in one
- use android phone for remote control



Single scan of stair case

[3] http://visionrobotics.de

Measurement principle of V&R MappingCube

- Rotating laser scanner
- Controller built into device
- Processing directly by system
- Registration right after scan
- registered scans available immediately after scan (e.g. on android phone)

Product details – see
http://www.vision-robotics.de

Object recognition

@Home
Furniture
People
Household articles

Rescue
Victims
Danger Signs
Gossow et al. (2008)
Obstacles
Stairs

Cars
Road signs
Roads
Cars
Pedestrians

Techniques:
Multi-Spectral, Color, Segmentation, Fusion

Joint work with

- Mihai Ivanovici, Brașov, România[4]
- Noël Richard, Poitiers, France[5]

Color information for image segmentation

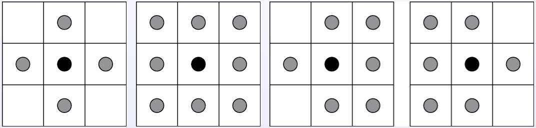
- textures
- fractal features
- graph cuts
- CSC — Priese and Rehrmann (1993)

- performance evaluation – *application specific* – *semantical*

→ unified, rigorous, formal description

[4] mihai.ivanovici@miv.ro
[5] richard@sic.univ-poitiers.fr

Neigborhoods I



(a) 4–connectivity (b) 8–connectivity (c) 6–connectivity

Fig.: Pixel neighborhoods

Neigborhoods II

Definition

We define that two pixel locations $P = (x, y)$ and $P' = (x', y')$ are k-neighbors if one belongs to the other's *k-connectivity*.

Definition

Let S be a sequence of pixel locations $[P_l]_{l=1...L}$; we call S *k-connected* if each pair of adjacent pixel locations is in a k neighborhood. We call a set of pixel locations $R = \{P_i\}$ *k-connected* if each pair P, P' of pixel locations from R there exists a *k-connected* path $S = [P_l]_{l=1...L}$; from P to P' which is completely in R, i.e. $P_1 = P$, $P_L = P'$, and $\forall l \in \{1, \dots, L\} : P_l \in R$.

Definition

Neigborhoods III

We call a set of connected pixels a *region*.

Homogeneity I

Simple classical definition

$$\gamma(R_i) = \begin{cases} \text{TRUE} & \text{if} \quad \forall P \in R_i : ||I(P) - \mu(R_i)|| \leq \theta \\ \text{FALSE} & \quad \text{otherwise} \end{cases} \quad , \quad (3)$$

$\mu(R)$ is the mean $\mu(R) = \frac{1}{||R||} \sum_{P' \in R} I(P')$, θ is some threshold.

Required:

- norm
- addition

(NB: not valid in HSV!)

Homogeneity II

Other homogeneity criteria

- texture
- fractal dimension
- other color spaces (L*a*b*, Luv)
- statistics

Color similarity:
Equidistant coordinates in RGB, YUV, XYZ do not define colors perceptually similar MacAdam (1942):
$\rightarrow$ **Color-specific distances: the ΔE family**[6]

[6] More in Sect. 12

CSC I

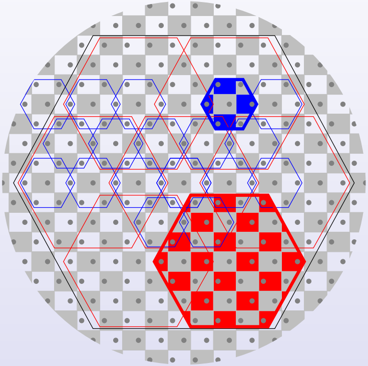


Fig.: Hexagonal hierarchical island structure for CSC and some code elements.

CSC II

The algorithm was introduced in Priese and Rehrmann (1993).

CSC III

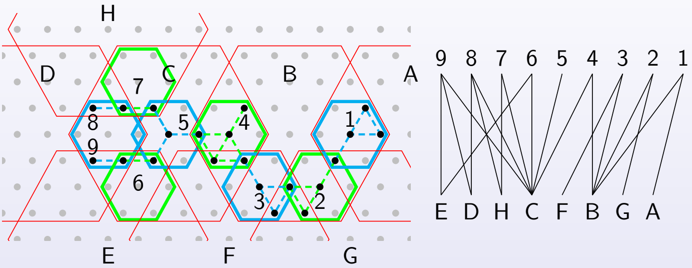


Fig.: Example of linked code elements and corresponding graph structure.

CSC IV

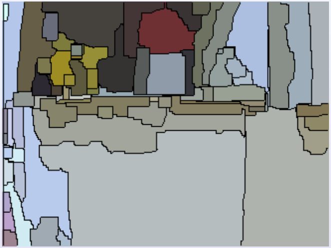
Properties

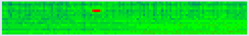
- very fast (almost real time)
- stable
- hierarchical / multi-resolution
- operates in spatial domain
- can use arbitrary criteria of homogeneity

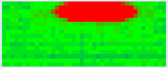
http://www.uni-koblenz-landau.de/koblenz/fb4/institute/icv/agpriese/do

`http://www.uni-koblenz-landau.de/koblenz/fb4/institute/icv/agpriese`

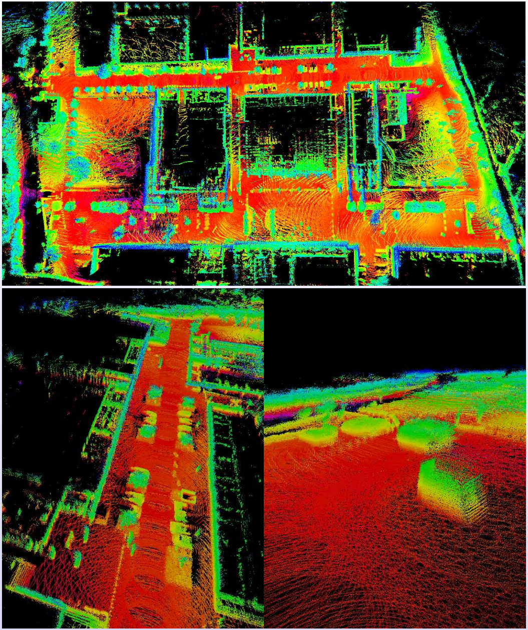
Victims





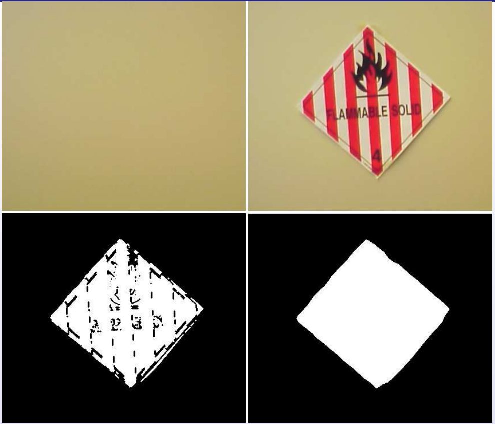


Color image – CSC – 180 scans – 60 scans



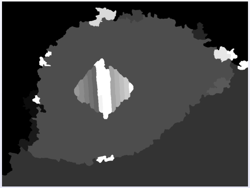
Result of 6D SLAM by A. Nüchter


FLAMMABLE SOLID
4
DANGEROUS WHEN WET
4
1.4
EXPLOSIVES
*
1
FLAMMABLE LIQUID
3
FLAMMABLE SOLID
4
OXIDIZER
5.1

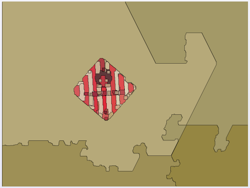


Color SURF Gossow et al. (2008)

input



jseg



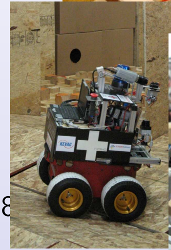
csc

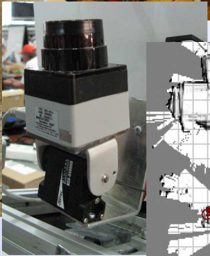
RoboCup Rescue

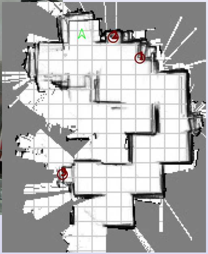
Robots as autonomous life savers

Results:

- flexible software architecture
- stable mapping
- Winner RoboCup GermanOpen 2007, 2008, 2009 & 2010 (autonomy)
- Winner RoboCup World Championship 2007 & 2008 (autonomy)







Summer School

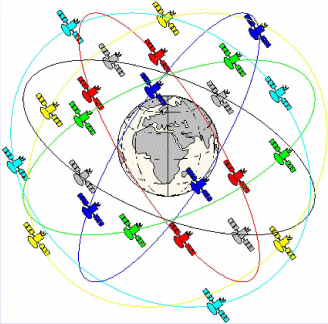
- 12.-16.09.2011 Workshop on Robotic Architectures ROS
- 19.-23.09.2011 ADAPT summerschool on *Cyber Physical Systems*

Grants for students and PhD students available!

http://www.uni-koblenz-landau.de/koblenz/fb4/institute/uebergreifend/adapt2011

Thanks for your attention!

GPS



[7]

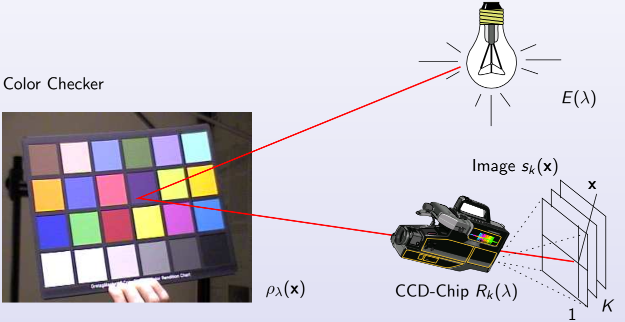
- System of 24 satellites
- radio signals
- transmit path parameters and GPS time

[7] http://www.landscaper.de/GPS_Navigation/GPS_Grundprinzip/gps_p5.gif

Problems with GPS

- Drift
- occlusion
- accuracy
- z-coordinate

Linear radiometric calibration



Discrete Device Sensitivity I

According to Alsam and Finlayson (2002): a sum of $L = 31$ samples

$$s_k(\mathbf{x}) = \sum_{\lambda=1}^{L} E_\lambda \cdot \rho_\lambda(\mathbf{x}) \cdot R_{k,\lambda} \cdot \Delta\lambda \quad . \tag{4}$$

Vector $\mathbf{E} = [E_\lambda]_{\lambda=1\ldots L}$: discrete spectral energy distribution for light,
Vector $\boldsymbol{\rho}(\mathbf{x}) = [\rho_\lambda(\mathbf{x})]_{\lambda=1\ldots L}$: discrete reflectance at position $\mathbf{x}$
Matrix $\mathbf{R} = [R_{k,\lambda}]_{k=1,\ldots,K,\lambda=1\ldots L}$ discrete spectral sensitivity curves of the sensors

Discrete Device Sensitivity II

Re-write matrix **R** as a vector

$$\mathbf{r} := (R_{1,1} \dots R_{1,L}, R_{2,1} \dots R_{2,L}, \dots R_{K,1} \dots R_{K,L})$$

Define a $(KN \times LK)$ - matrix **A** consisting of sensor responses measured at N points of either zeros or products $E_\lambda \cdot \rho_\lambda$

$$\mathbf{s} = \mathbf{A}\mathbf{r} \tag{5}$$

Discrete Device Sensitivity III

In Paulus et al. (2002)

- Instead of iterative optimization techniques weaker constraints lead to a linear problem
- solved using $\mathrm{SVD}(\mathbf{A}) = \mathbf{U\Sigma V}^\mathsf{T}$
- derive a linear approximation of calibration parameters

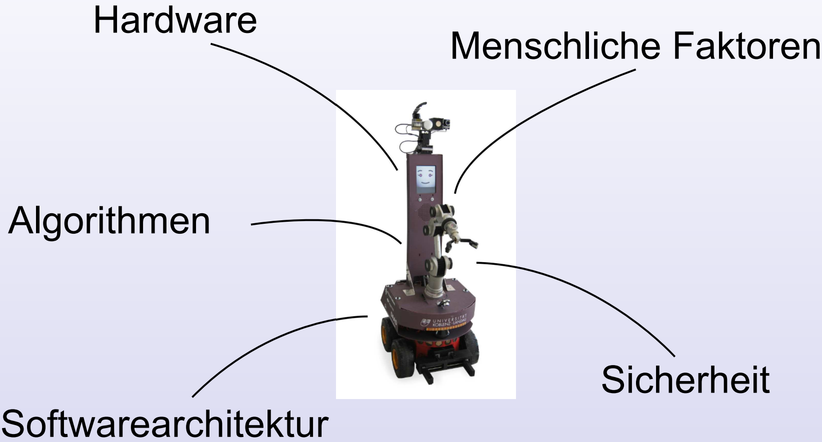
$$\mathbf{r} = \left(\mathbf{VP\Sigma}^2\mathbf{V}^\mathsf{T} + \mu \cdot \mathbf{G}\right)^{-1}\mathbf{VP\Sigma U}^\mathsf{T}\mathbf{s} \quad . \tag{6}$$

with

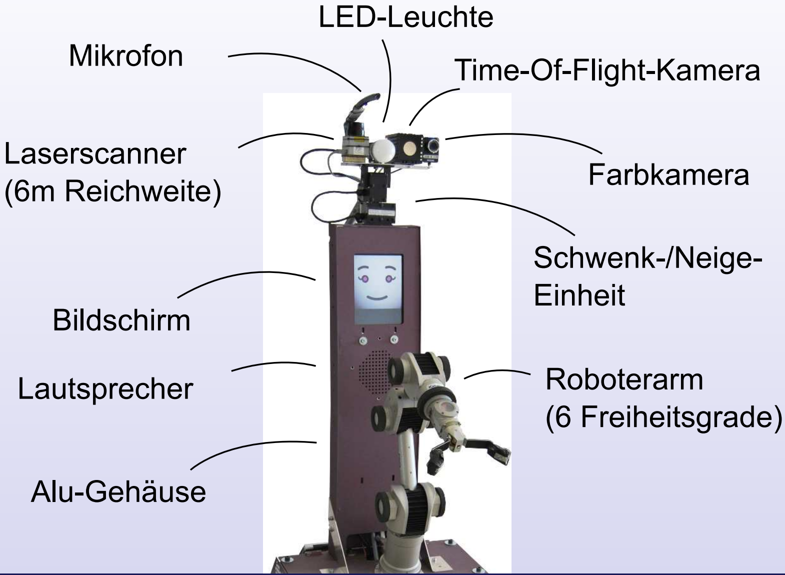
- Regularization parameter μ
- Matrix $\mathbf{P}$ to enforce rank

Lisa

Challenges


Hardware
Menschliche Faktoren
Algorithmen
Sicherheit
Softwarearchitektur

Hardware I


LED-Leuchte
Mikrofon
Time-Of-Flight-Kamera
Laserscanner
(6m Reichweite)
Farbkamera
Schwenk-/Neige-
Einheit
Bildschirm
Lautsprecher
Roboterarm
(6 Freiheitsgrade)
Alu-Gehäuse

Hardware II

Laptop

Farbkamera

LED-Leiste

Laserscanner
(30m Reichweite)

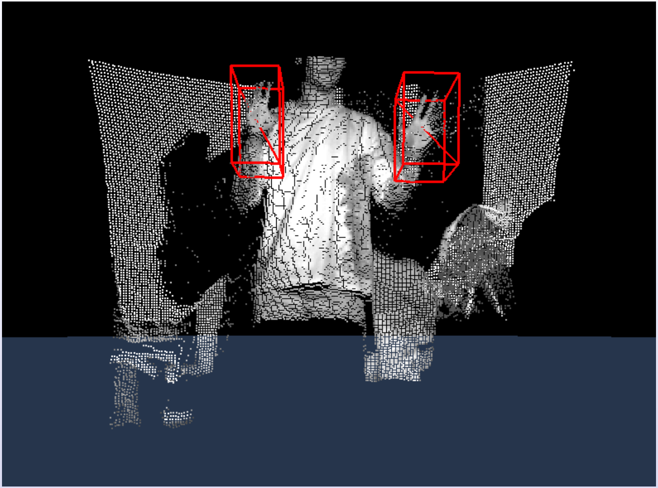
Differential-
antrieb

Sonarsensoren

Mobile Plattform:
Pioneer 3-AT

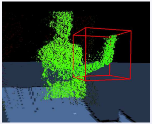
Greifer (2 Freiheitsgrade)

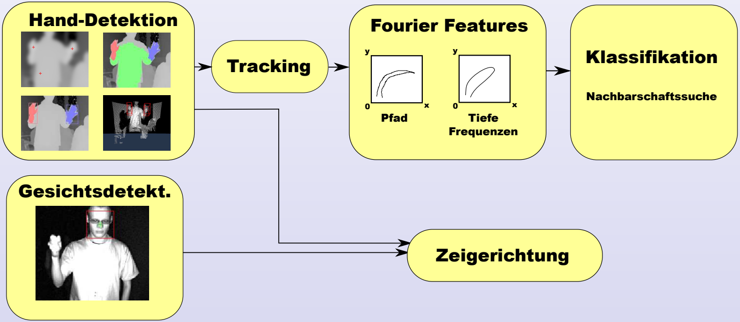
Gesture recognition



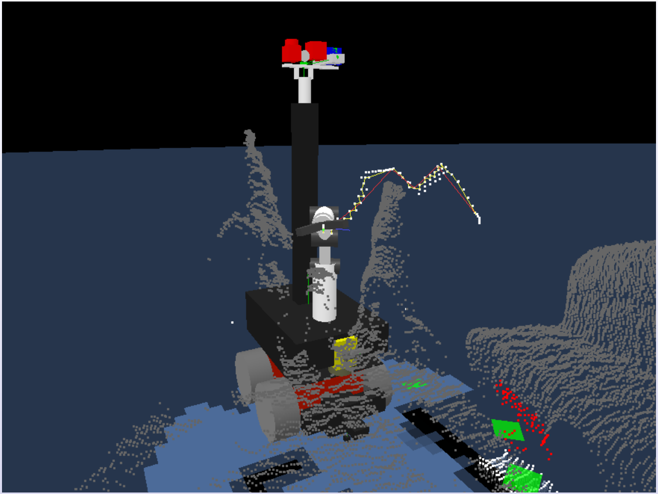
Gesture recognition

Time-Of-Flight-
Kamera

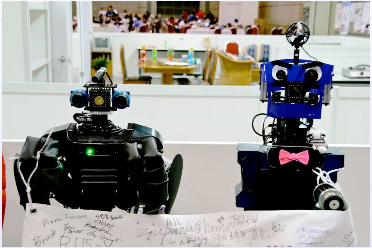


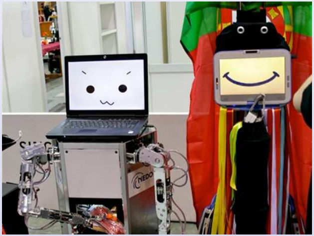


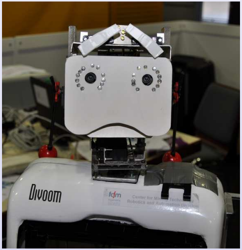
Grasp objects



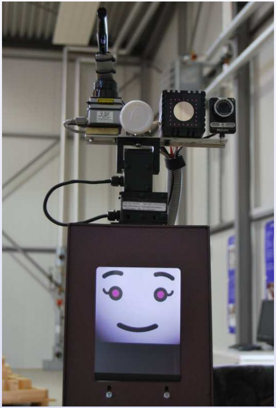
MMI

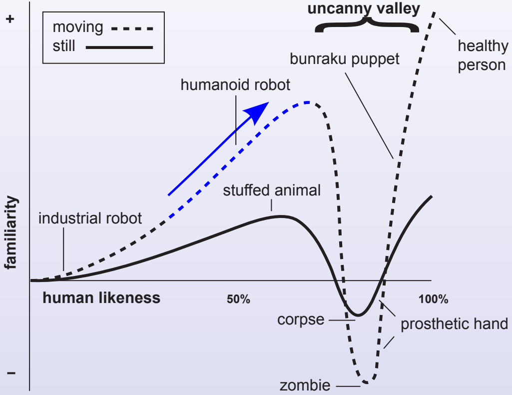






MMI




uncanny valley
moving
still
healthy person
bunraku puppet
humanoid robot
stuffed animal
industrial robot
familiarity
+
-
human likeness
50%
100%
corpse
prosthetic hand
zombie

Safety

Definition

A discrete *image* I is a function $I : \mathbb{N}^2 \to \mathbb{V}$. *Locations* P belong to the image support, i.e. a finite rectangular grid, i.e. $D = [0, \dots M] \times [0, \dots N] \subseteq \mathbb{N}^2$. For *gray-scale* images $\mathbb{V} = [0, \dots, 255] \subseteq \mathbb{N}$; for *color images* we (usually) have $\mathbb{V} = [0, \dots, 255]^3 \subseteq \mathbb{N}^3$. An image element X is called a *pixel* which has a *pixel location* $\Lambda(X) = P$ and a *pixel value* $\Upsilon(X) = I(\Lambda(X)) = v \in \mathbb{V}$.

Segmentation of an image I:
image is decomposed into a number N_{R} of regions R_i, with $i = 1..N_{\mathrm{R}}$, which are disjoint non-empty sections of I .

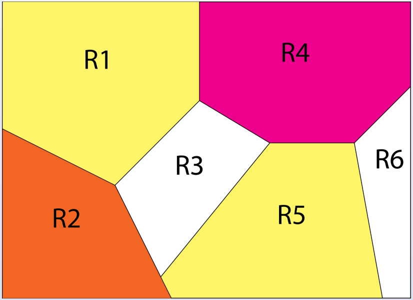


Fig.: Theoretical example of segmentation.

Regions are *connected* sets of pixel locations that exhibit some similarity in the pixel *values* which can be defined in various ways.

The segmentation of an image I into regions R_i is called *complete*, if the regions exhibit the properties of Fu and Mui (1981) formalized in the following:

Definition

Region Label Image I_{R}: result of segmentation.
$I_{\mathrm{R}} : \mathbb{N}^2 \rightarrow \{1, \dots, N_{\mathrm{R}}\}$.
This label image is also called a *map*.

Distances and Measures I

Equidistant coordinates in RGB, YUV, XYZ do not define colors perceptually similar MacAdam (1942).

Color-specific distances: the ΔE family

$$\Delta E = \sqrt{(L_1^* - L_2^*)^2 + (a_1^* - a_2^*)^2 + (b_1^* - b_2^*)^2} \quad . \tag{7}$$

Distances and Measures II

Physiologically, the eye is more sensitive to hue differences than chroma and lightness and ΔE does not take this aspect into account.
Improvements by CIE: ΔE_{94} and finally ΔE_{2000}

$$\Delta E_{94} = \sqrt{\left(\frac{\Delta L}{K_L S_L}\right)^2 + \left(\frac{\Delta C}{K_C S_C}\right)^2 + \left(\frac{\Delta H}{K_H S_H}\right)^2} \quad , \qquad (8)$$

Color Textures I

For a set Q of N pixel locations $Q = \{P_1, P_2, ..., P_N\}$ let m be the mean position of all pixels: $m = \frac{1}{N}\sum_{i=1}^{N} P_i$. If Q is classified into C classes Q_i according to the color values at those locations, then let m_i be the mean position of the N_i points of class Q_i: $m_i = \frac{1}{N_i}\sum_{P \in Q_i} P_i$. Then let $S_\mathrm{T} = \sum_{q \in Q} ||q - m||^2$, the total spatial variance and

$$S_\mathrm{W} = \sum_{i=1}^{C} S_i = \sum_{i=1}^{C} \sum_{q \in Q_i} ||q - m_i||^2 \quad , \tag{9}$$

the spatial variance relative to the Q_i classes. The measure J is defined as:

$$J = \frac{S_B}{S_\mathrm{W}} = \frac{S_\mathrm{T} - S_\mathrm{W}}{S_\mathrm{W}} \quad , \tag{10}$$

Color Textures II

The *J-image* is a gray-scale pseudo-image whose pixel values are the J values calculated over local windows centered on each pixel position. The higher the local J value is, the more likely that the pixel is near region boundaries.

(a) 5×5 (b) 9×9 (c) 21×21

Fig.: J-images for three sizes of the local window.

Own Publications I

L. Csink, Dietrich Paulus, Ulrike Ahlrichs, and Benno Heigl. Color Normalization and Object Localization. In Volker Rehrmann, editor, *Vierter Workshop Farbbildverarbeitung*, pages 49–55, Koblenz, 1998. F"olbach.

Peter Decker, Dietrich Paulus, and Tobias Feldmann. Dealing with degeneracy in essential matrix estimation. In *Proceedings of the International Conference on Image Processing (ICIP 2008)*, pages 1964–1967, San Diego, California, U.S.A., 2008. IEEE Press.

D. Gossow, J. Pellenz, and D. Paulus. Danger sign detection using color histograms and surf matching. In *International Workshop on Safety, Security and Rescue Robotics*, 2008.

David Gossow, Peter Decker, and Dietrich Paulus. Extending surf to the color domain. In *CGIV 2010 - Fifth European Conference on Colour in Graphics, Imaging and Vision*, pages 215–221, 2010.

Own Publications II

Christian Münzenmayer, Dietrich Paulus, and Thomas Wittenberg. A spectral color correction framework for medical applications. *IEEE Transactions on Biomedical Engineering*, 53(2):254– 265, 2006.

Andreas Nüchter, Jan Elseberg, Peter Schneider, and Dietrich Paulus. Linearization of rotations for globally consistent n- scan matching. In *Proceedings of the IEEE International Conference Robotics and Automation (ICRA '10)*, pages 1373–1379, Anchorage, Alaska, 2009.

Andreas Nüchter, Jan Elseberg, Peter Schneider, and Dietrich Paulus. Linearization of rotations for globally consistent n- scan matching. In *Proceedings of the IEEE International Conference Robotics and Automation (ICRA '10)*, pages 1373–1379, Anchorage, Alaska, 2010.

Dietrich Paulus. *Aktives Bildverstehen*. Der Andere Verlag, Osnabrück, 2001.

Dietrich Paulus, Andreas Winzen, and H. Niemann. Knowlege based object recognition and model generation. In Donald W. Braggins, editor, *Proceedings Europto 93, Computer Vision for Industry, München*, pages 382–393, Bellingham, WA, 1993. SPIE. Proceedings 1659.

Own Publications III

Dietrich Paulus, Joachim Hornegger, and L. Csink. Linear approximation of sensitivity curve calibration. In K.-H. Franke, editor, *8. Workshop Farbbildverarbeitung*, pages 3–10, Ilmenau, 2002. Schriftenreihe des Zentrums f"ur Bild- und Signalverarbeitung.

Johannes Pellenz and Dietrich Paulus. Stable mapping using a hyper particle filter. In *RoboCup Symposium 2009*, 2009.

Other Publications I

A. Alsam and G. Finlayson. Recovering spectral sensitivities with uncertainty. In *CGIV*, pages 22–26, Poitiers, France, 2002. IS&T.

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