



KR II: Räumliche Kognition

Prof. Dr. Verena Hafner,
Humboldt-Universität zu Berlin, Institut für Informatik,
WS 2008/2009

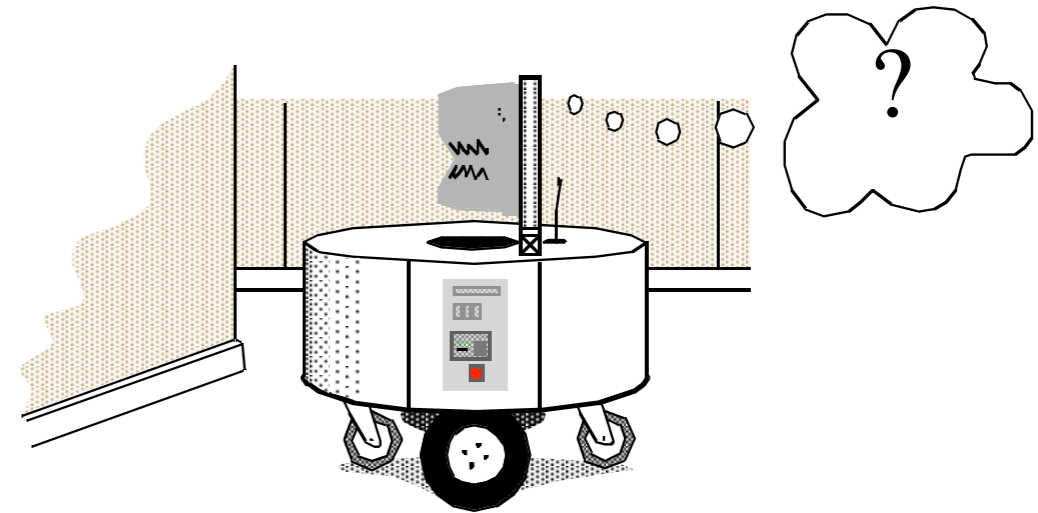
Motivation

Evolutionary pressure for the evolution of brains.
"Why don't plants have brains? [...] The answer is quite simple – they do not have to move and that is what brains are for." [Lewis Wolpert]



Navigation

- Standard Sichtweise:
 - Wo bin ich?
 - Wo sind andere Orte relativ zu mir?
 - Wie komme ich zu anderen Orten von hier?



[Levit and Lawton]



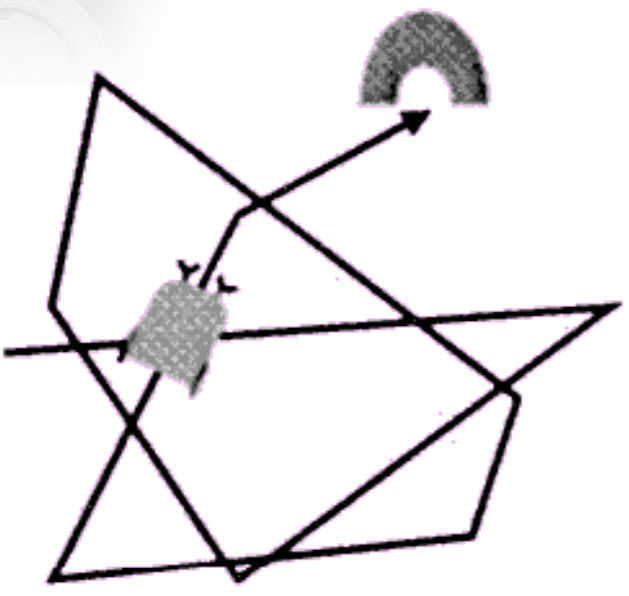
Navigation

- „Wo bin ich?“ ist oft irrelevant
- **WICHTIG:** „Wie komme ich ans Ziel?“
- „Navigation is the process of determining and maintaining a course or trajectory to a goal location“ [Franz, Mallot from Gallistel]



Navigation Hierarchy

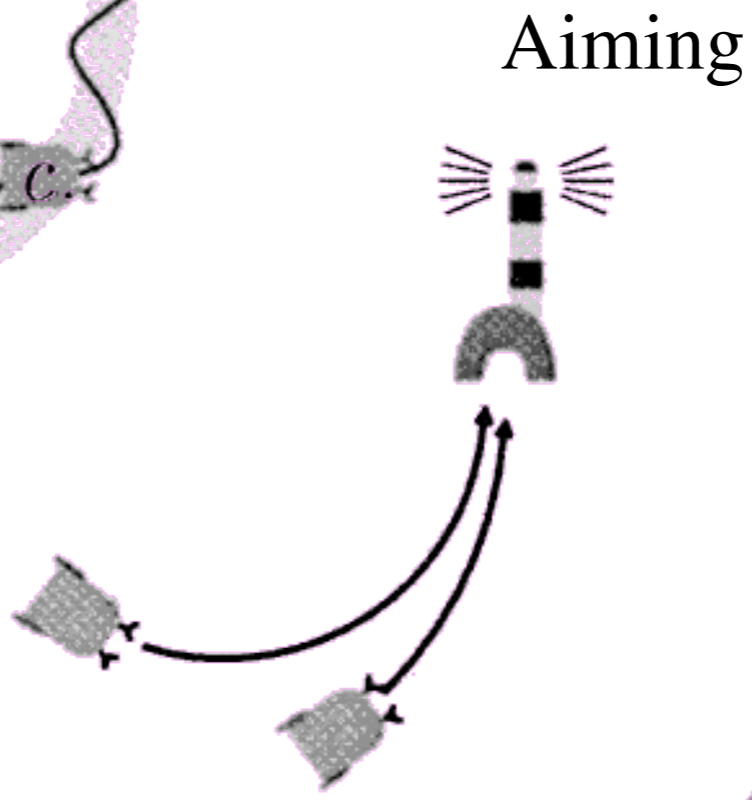
local



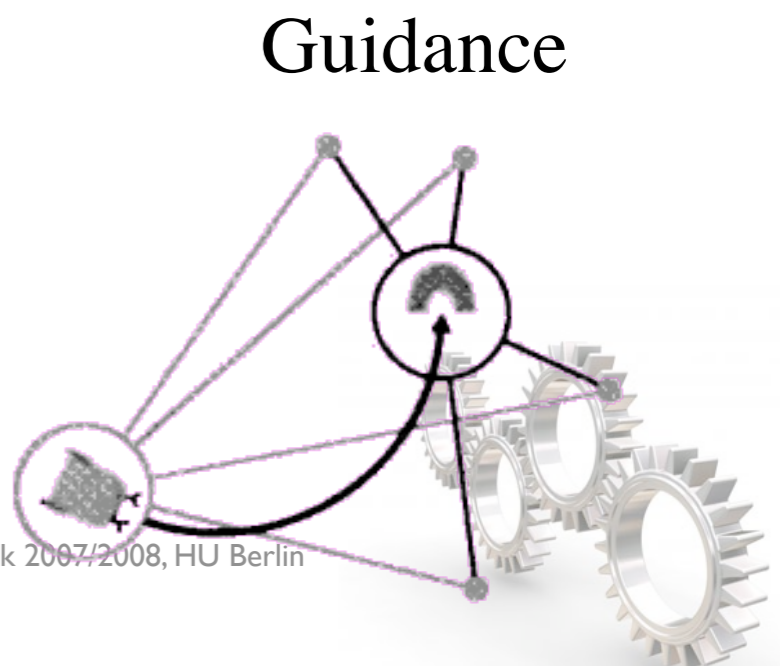
Search



Direction following



Aiming

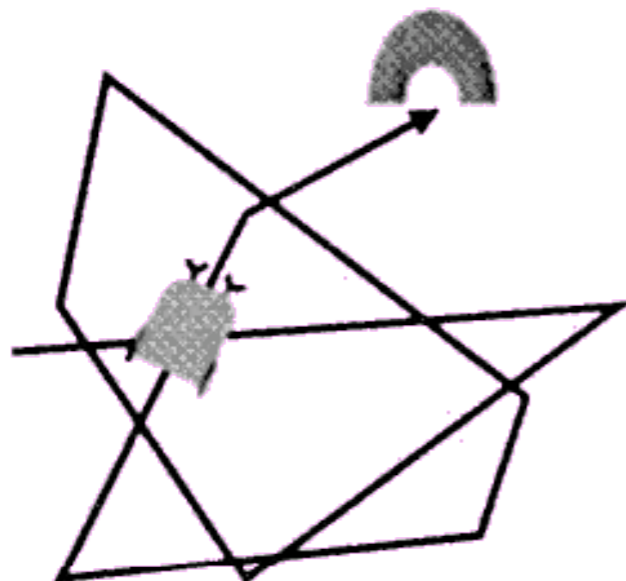


Guidance

(adapted from Franz and Mallot, 2000)

Navigation Hierarchy

local



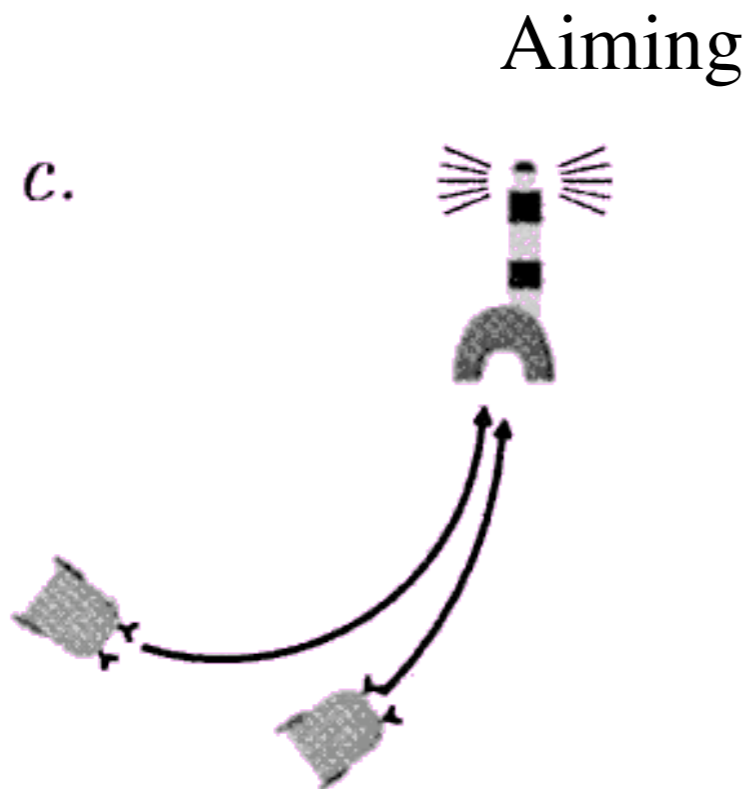
Search

- Random Search
- Bsp: Ameisen
- Spiralen
- Strategien?



Navigation Hierarchy

local



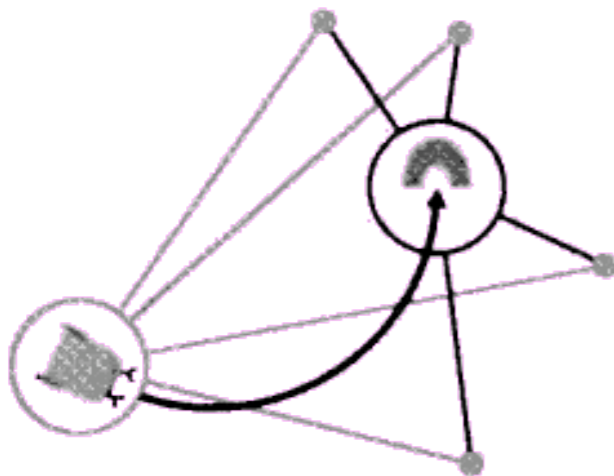
- Sichtbare Landmarke
- lokal/global
- catchment area
- Gradientensuche (z.B. olfaktorisch)



Navigation Hierarchy

local

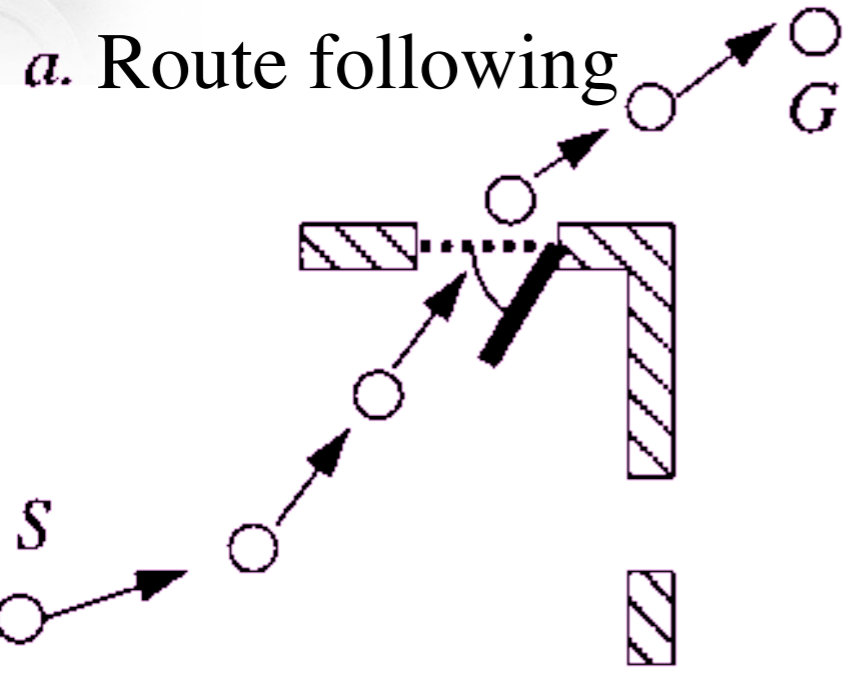
Guidance



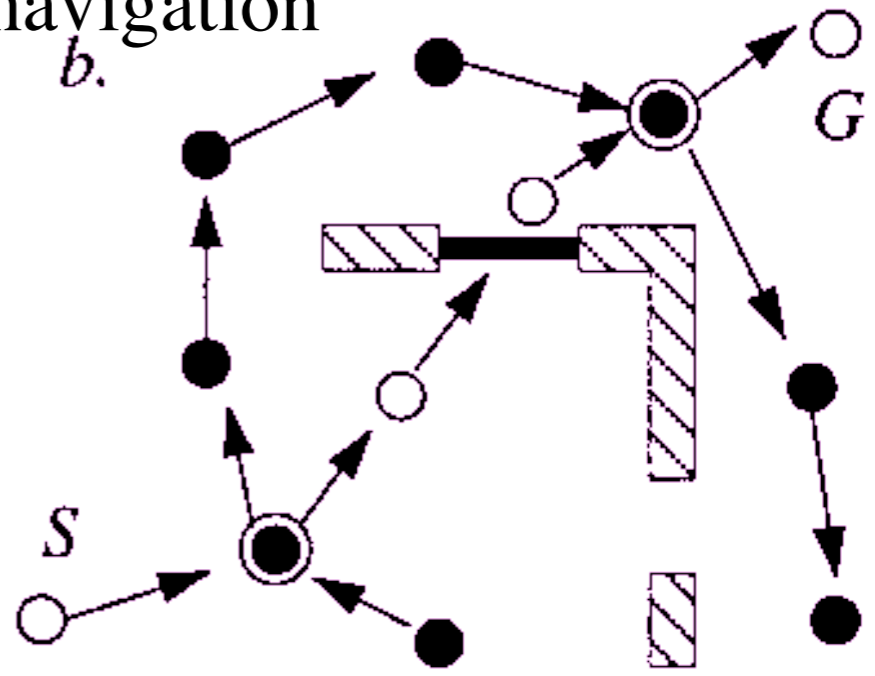
- Ziel ist relativ zu anderen Orten bekannt
- Visuelles Homing (später)



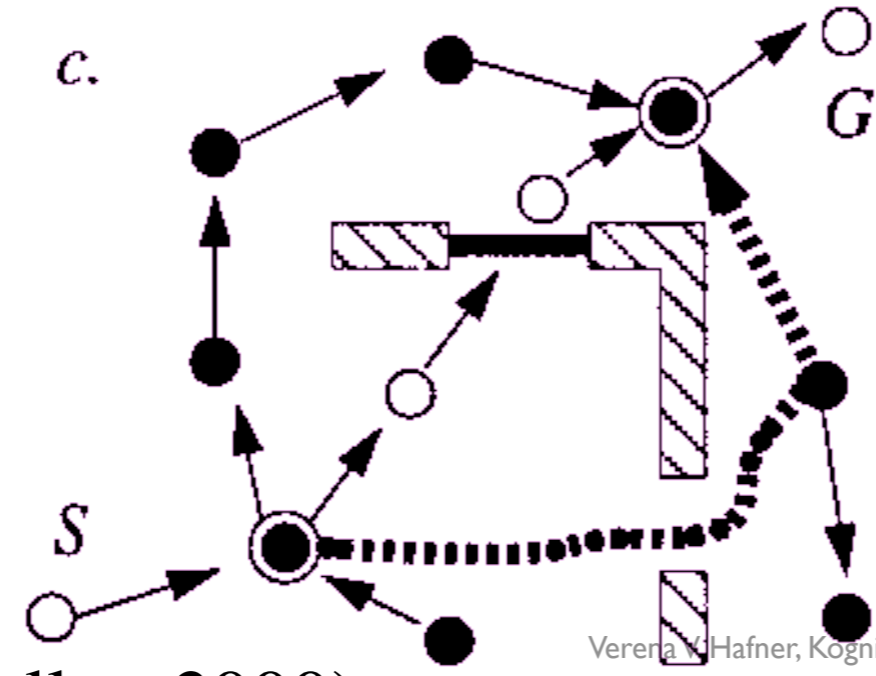
Navigation Hierarchy: wayfinding



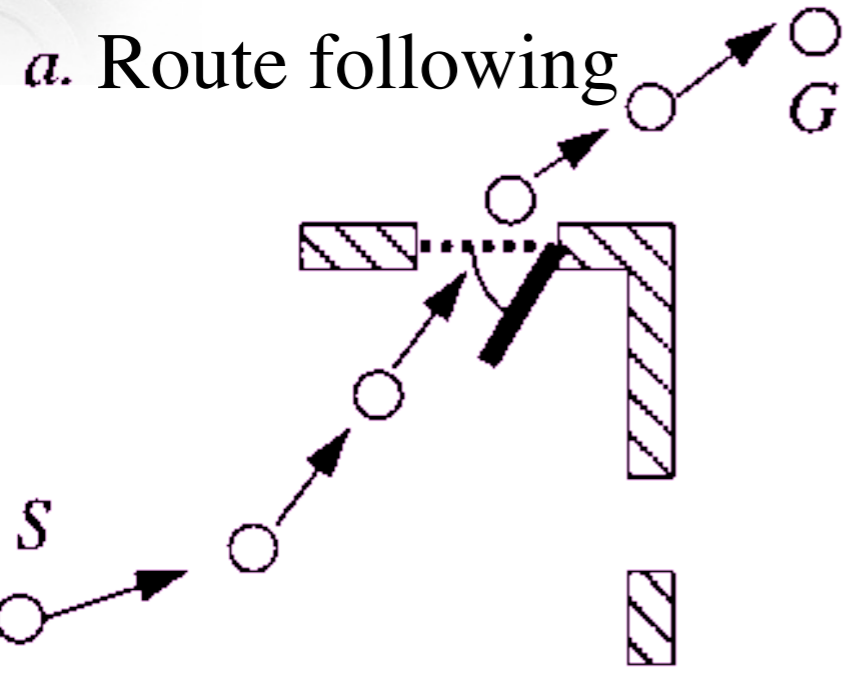
Topological navigation



Survey navigation



Navigation Hierarchy: wayfinding



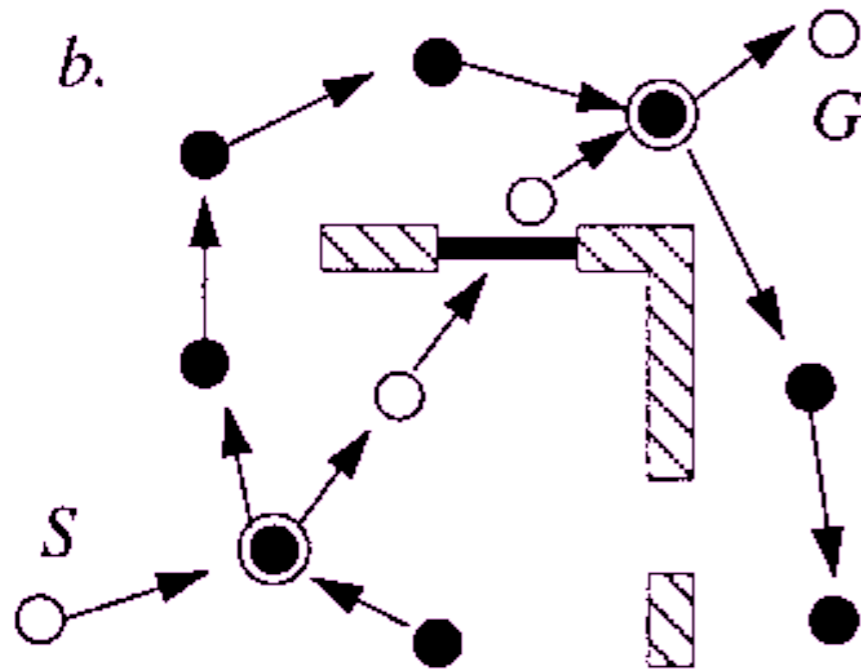
- Lokale Navigation zwischen mehreren Orten
- fehleranfällig

(adapted from Franz and Mallot, 2000)



Navigation Hierarchy: wayfinding

Topological navigation

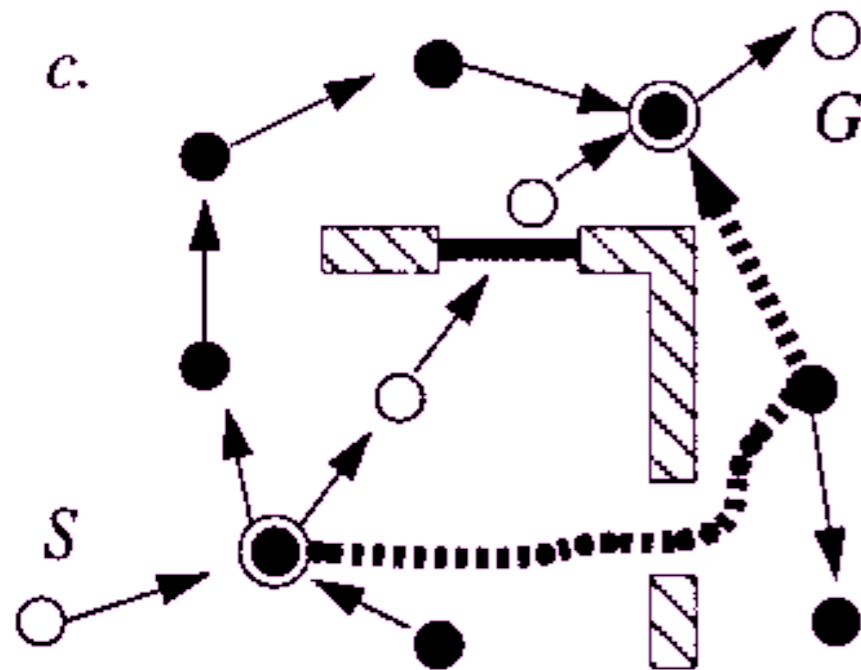


- Karte als Graph
- Entscheidungsmöglichkeiten an einzelnen Knoten
- Umwege



Navigation Hierarchy: wayfinding

Survey navigation



- Komplexeste Art der Navigation
- Umwege und Abkürzungen möglich
- zusätzliche metrische Information



Navigations-Hierarchie

The navigation hierarchy²

	Behavioural prerequisite	Navigation competence
Search	Goal recognition	Finding the goal without active goal orientation
Direction-following	Align course with local direction	Finding the goal from one direction
Aiming	Keep goal in front	Finding a salient goal from a catchment area
Guidance	Attain spatial relation to the surrounding objects	Finding a goal defined by its relation to the surroundings
Recognition-triggered response	Association sensory pattern–action	Following fixed routes
Topological navigation	Route integration, route planning	Flexible concatenation of route segments
Survey navigation	Embedding into a common reference frame	Finding paths over novel terrain

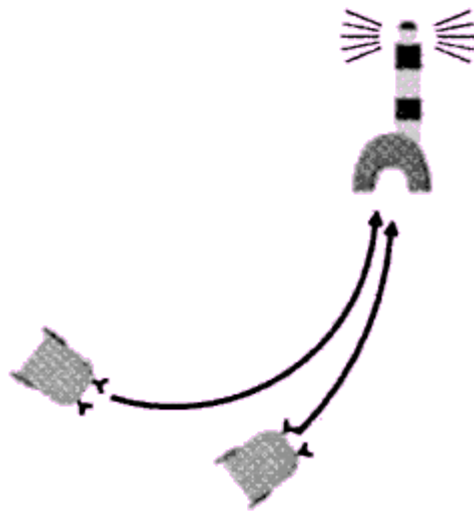
²Navigation behaviours are classified according to navigation competences that can be tested experimentally. The upper half of the table contains local navigation behaviours, the lower half way-finding behaviours.

(Franz and Mallot, 2000)

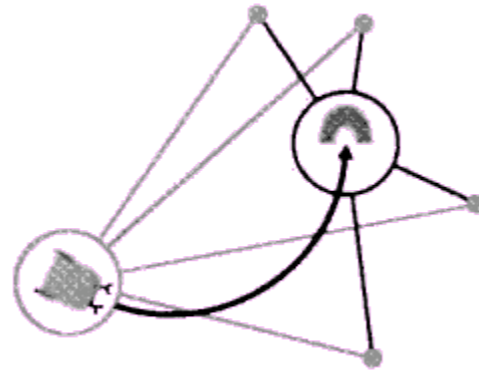


Modelle

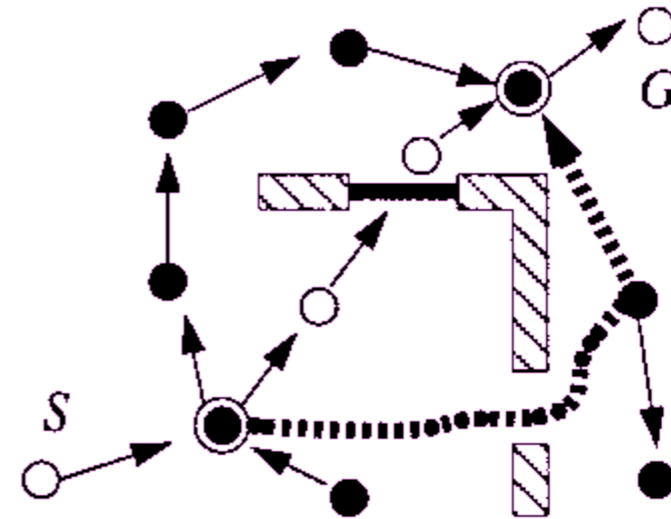
Aiming



Guidance



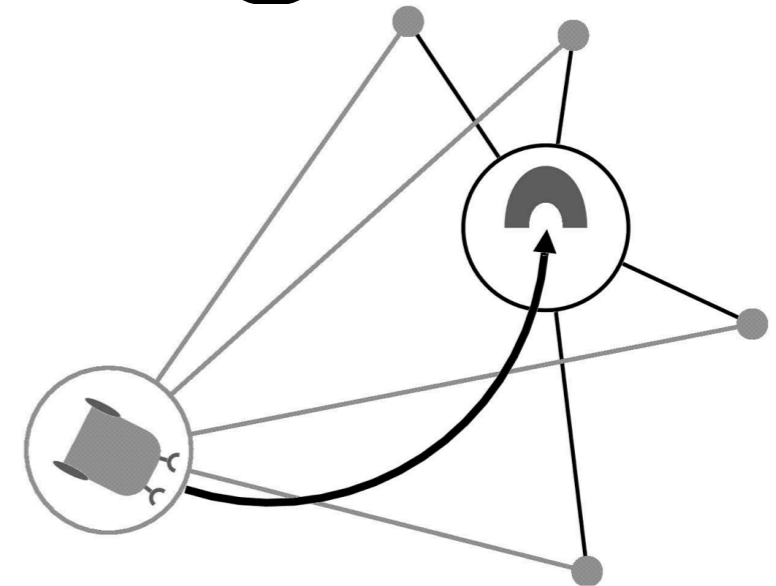
Survey navigation



(adapted from Franz and Mallot, 2000)



Visuelles Homing

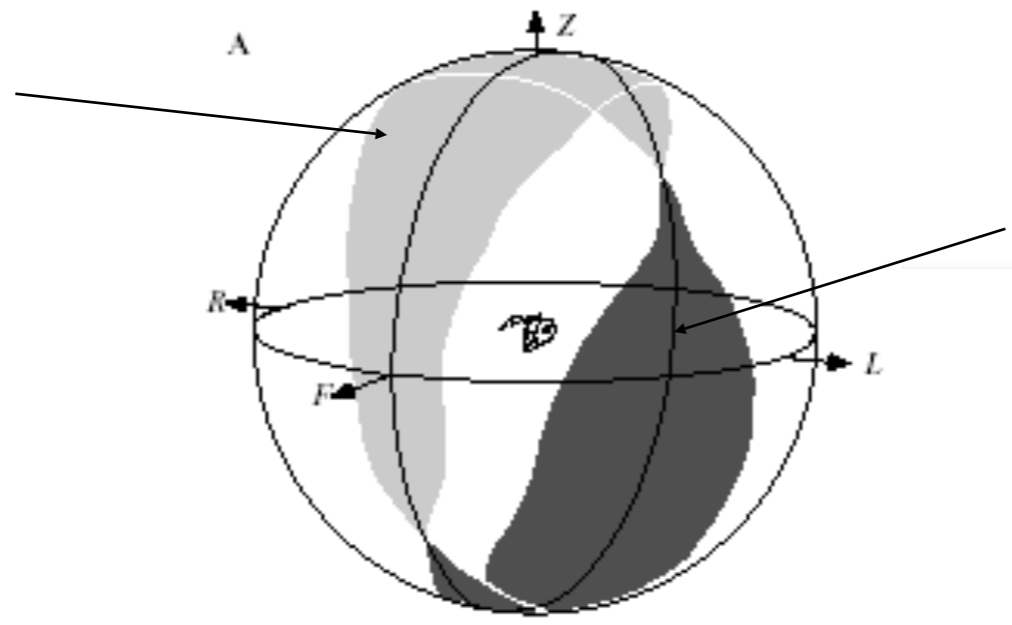


- Führung / guidance
- Zielpunkt selbst ohne auffälliges Merkmal
- Agent "geführt" von Anordnung von "Landmarken"
- Wiederherstellen einer bestimmten egozentrischen Beziehung zu den Landmarken



Visual Homing: Insect Inspiration

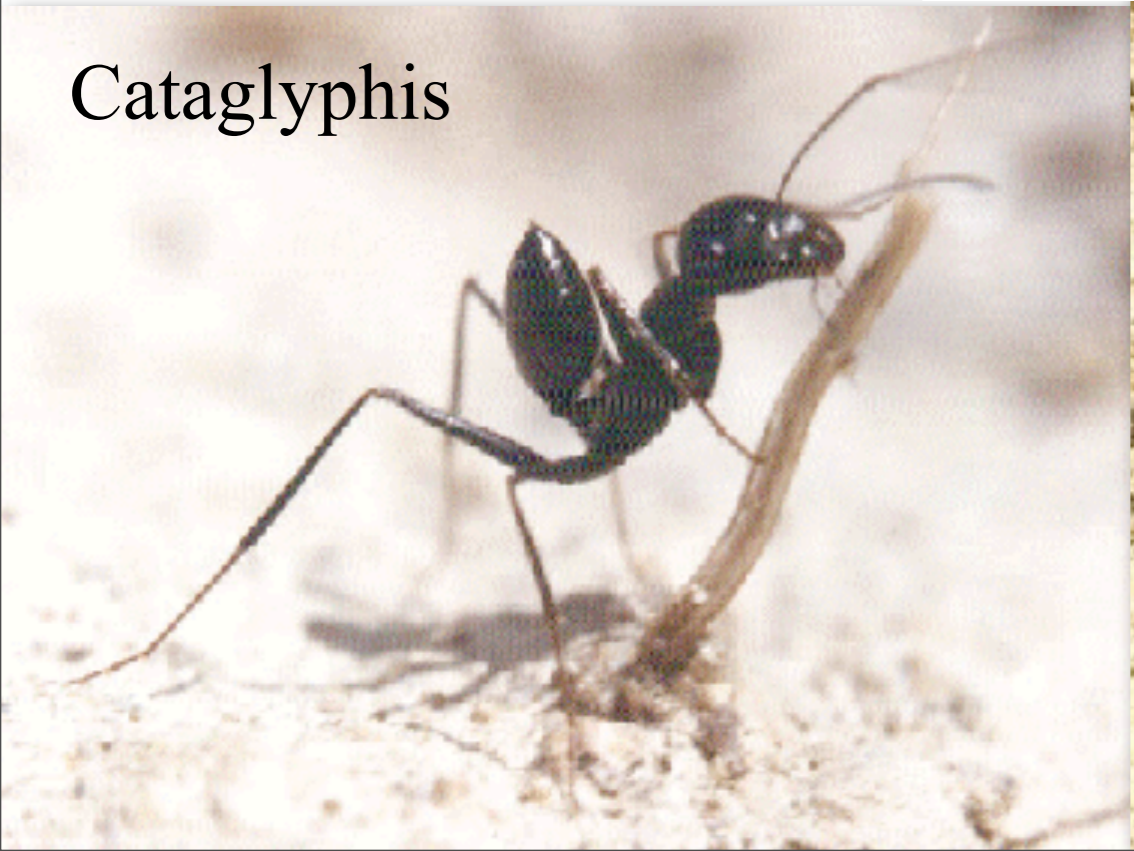
Binocular area



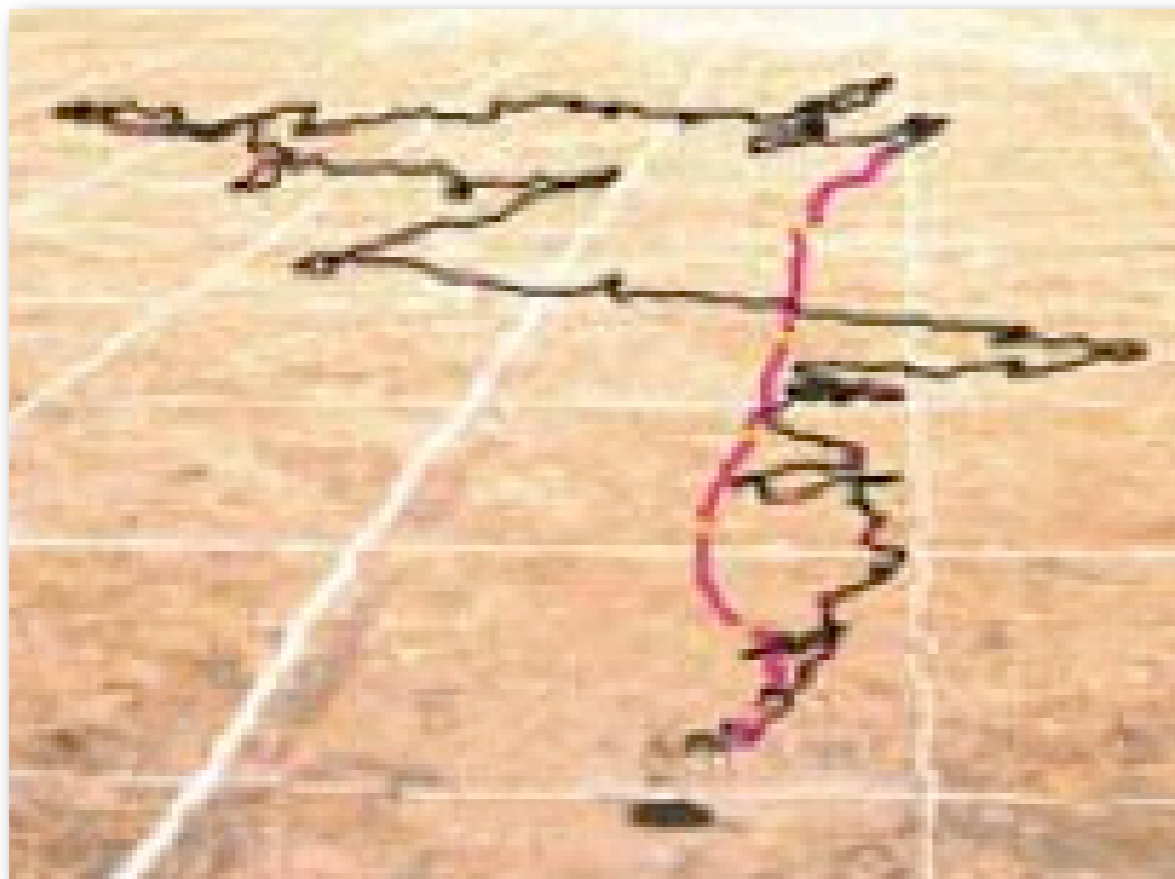
Blind area



Cataglyphis



Cataglyphis



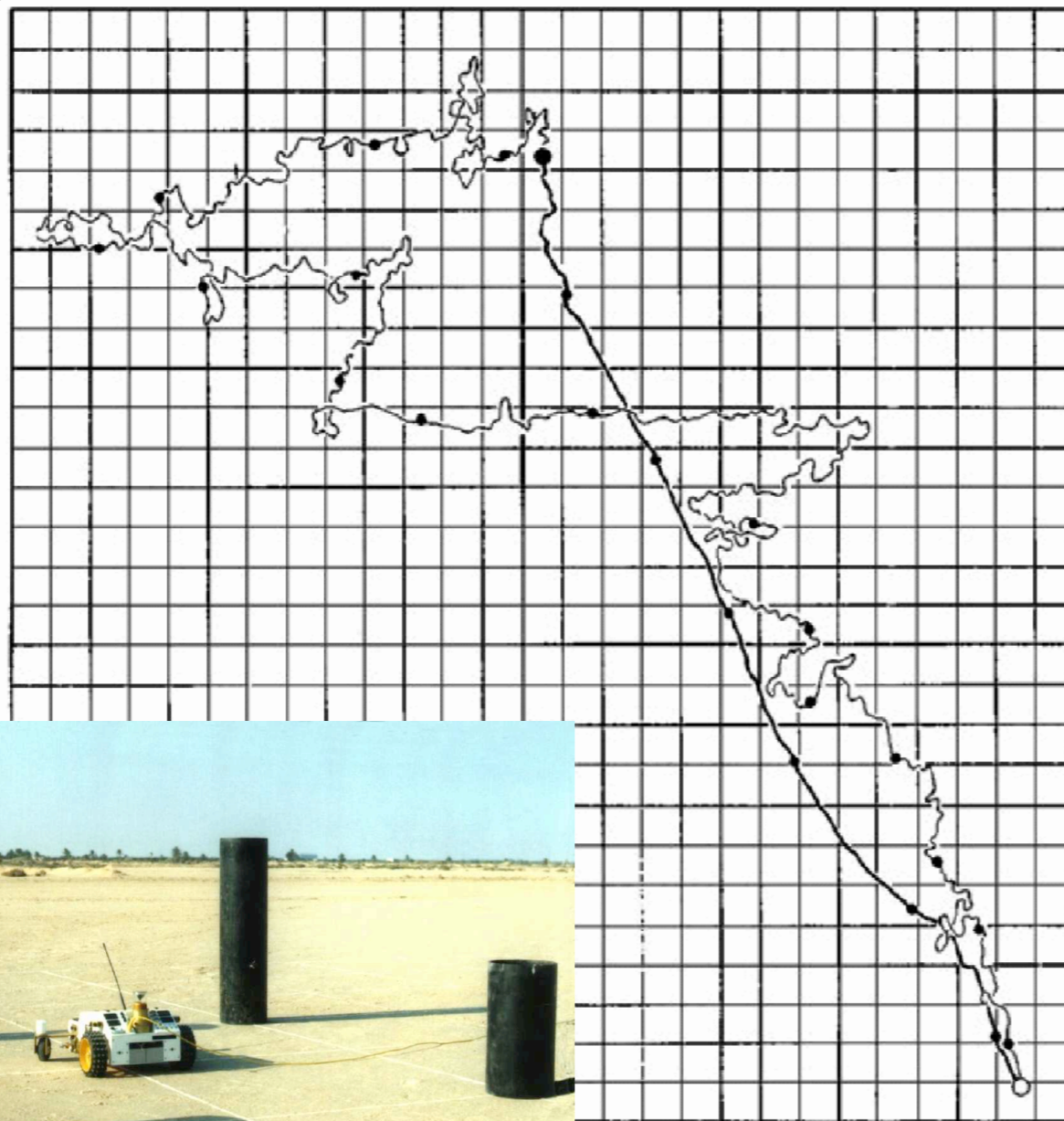
Pfadintegration



visuelle Navigation

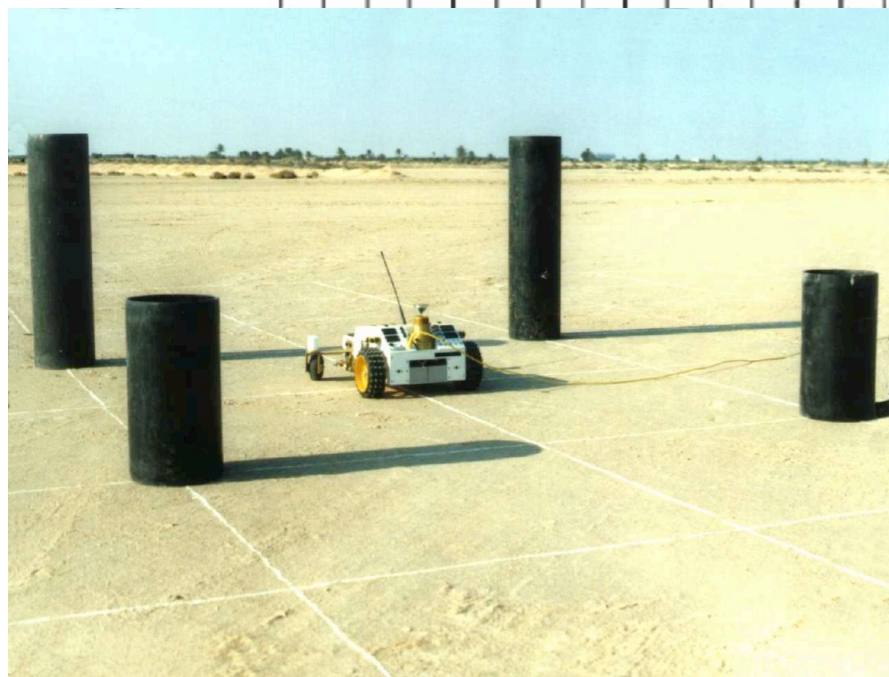


Cataglyphis - Navigations-Methoden



3 Navigationsmethoden:

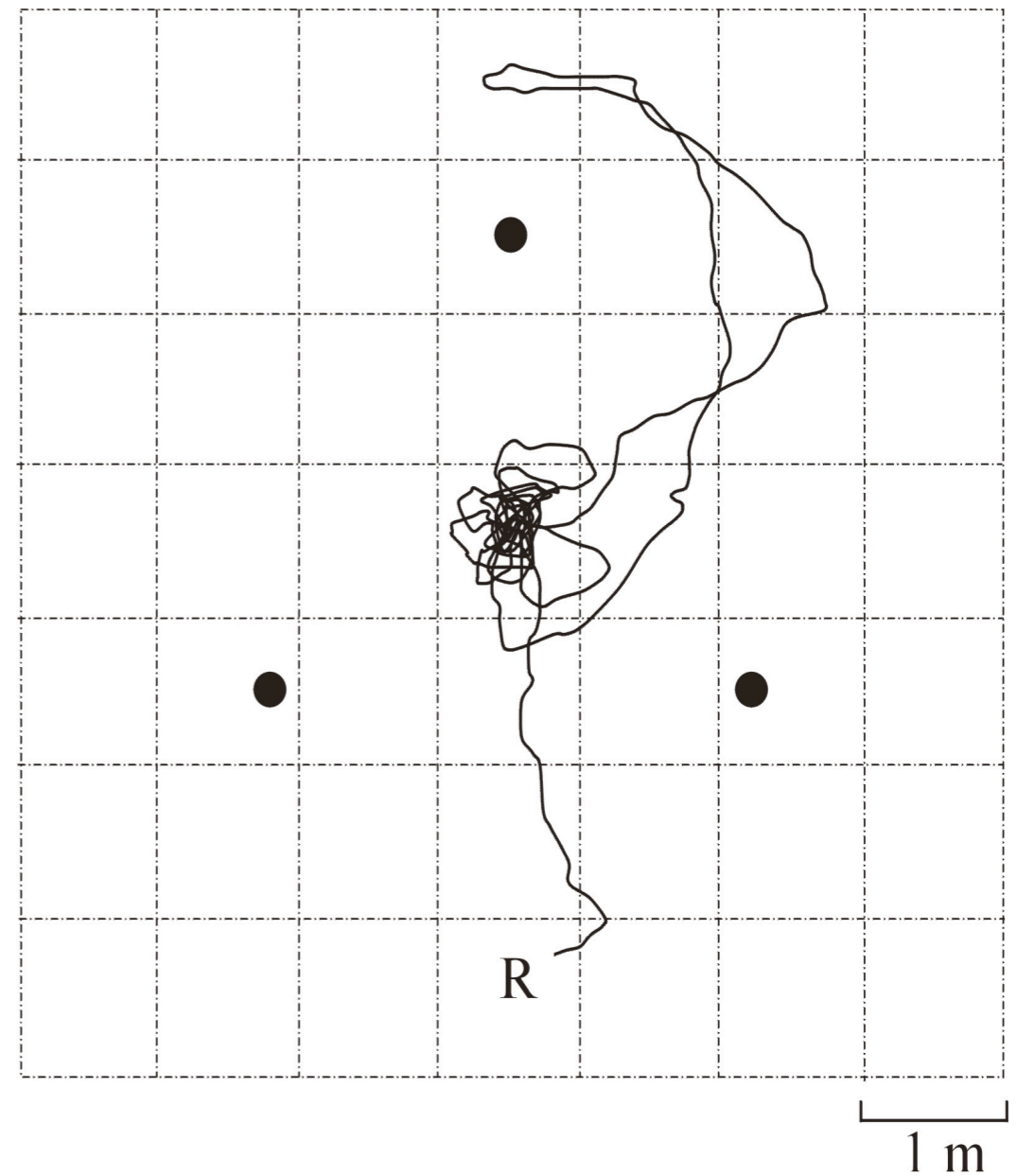
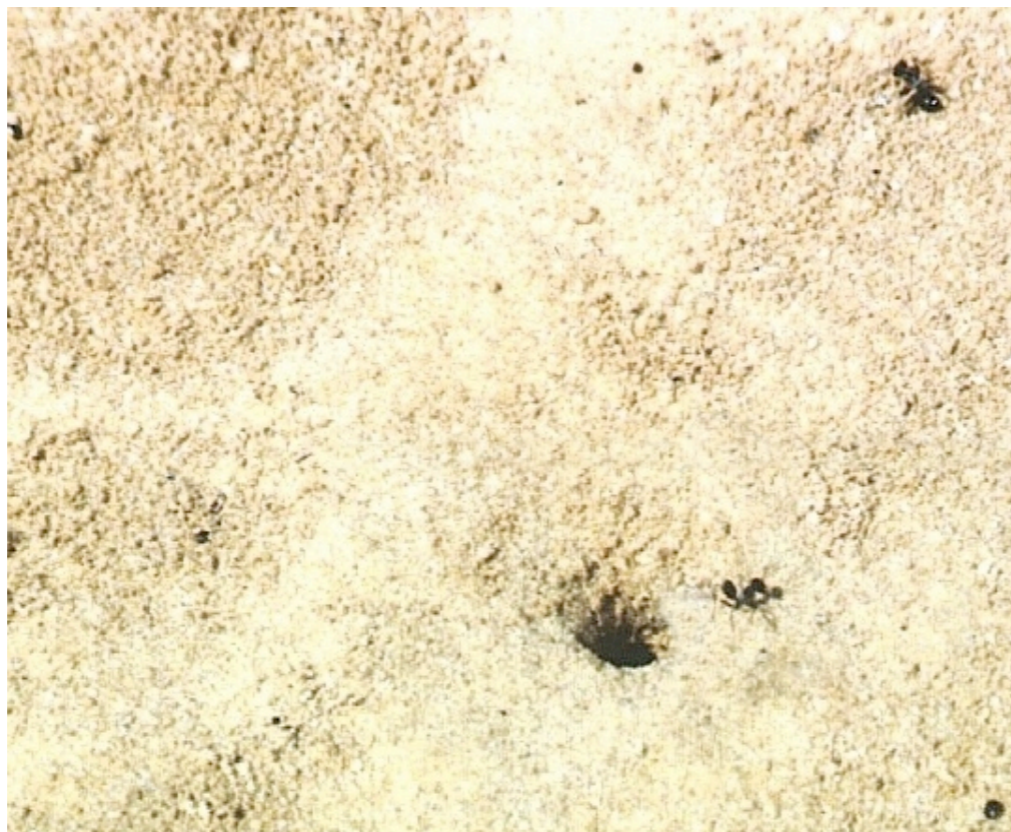
- Pfadintegration mit polarisiertem Licht Kompass
- Visuelle Landmarken Navigation
- Festes Suchmuster



© R. Wehner



Visuelle Landmarken Navigation: Ameisen

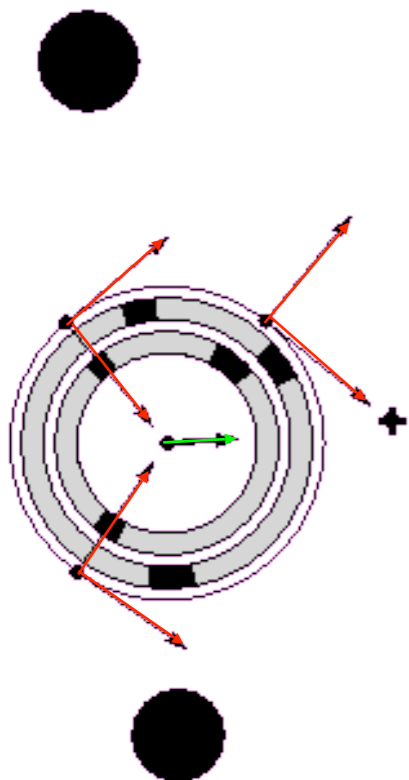


Testen von biologischen Hypothesen

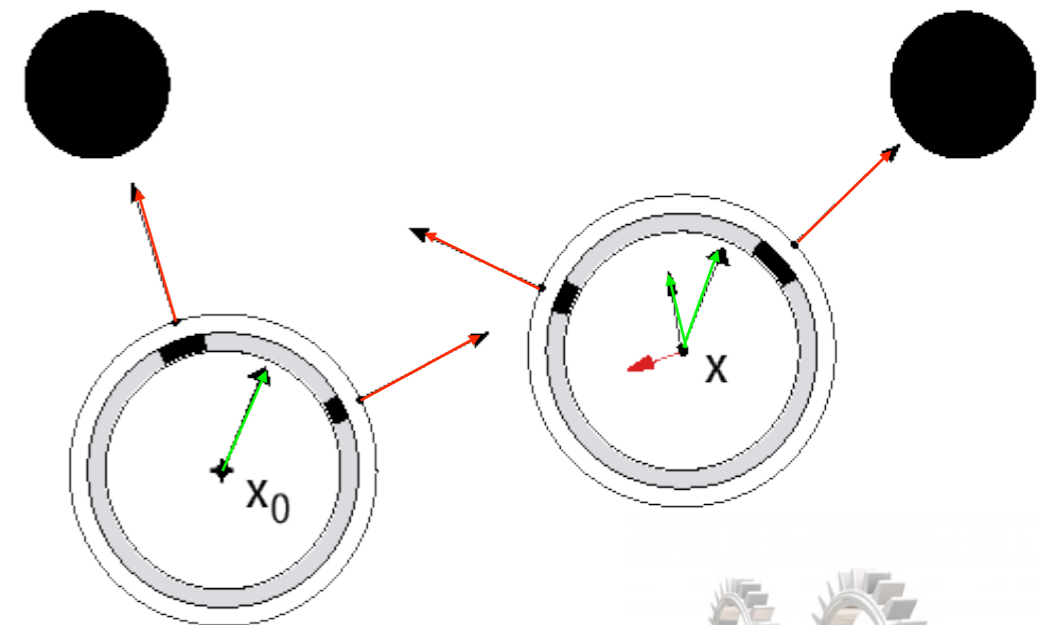


Modelle Visuellen Homings

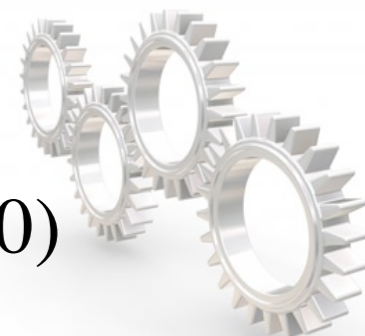
- Snapshot Model (Cartwright & Collett, 1983, 1987)
- ALV Model (Lambrinos et al., 2000)
- Warping Model (Franz et al. 1998)



(Cartwright and Collett, 1983, 1987)



Verena V. Hainel, Kopplings-Reportik 2007/2008, HU Berlin (Lambrinos et al., 2000)



Berechnung des Home Vektors

- Ist die „Wo bin ich?“-Frage noch relevant?

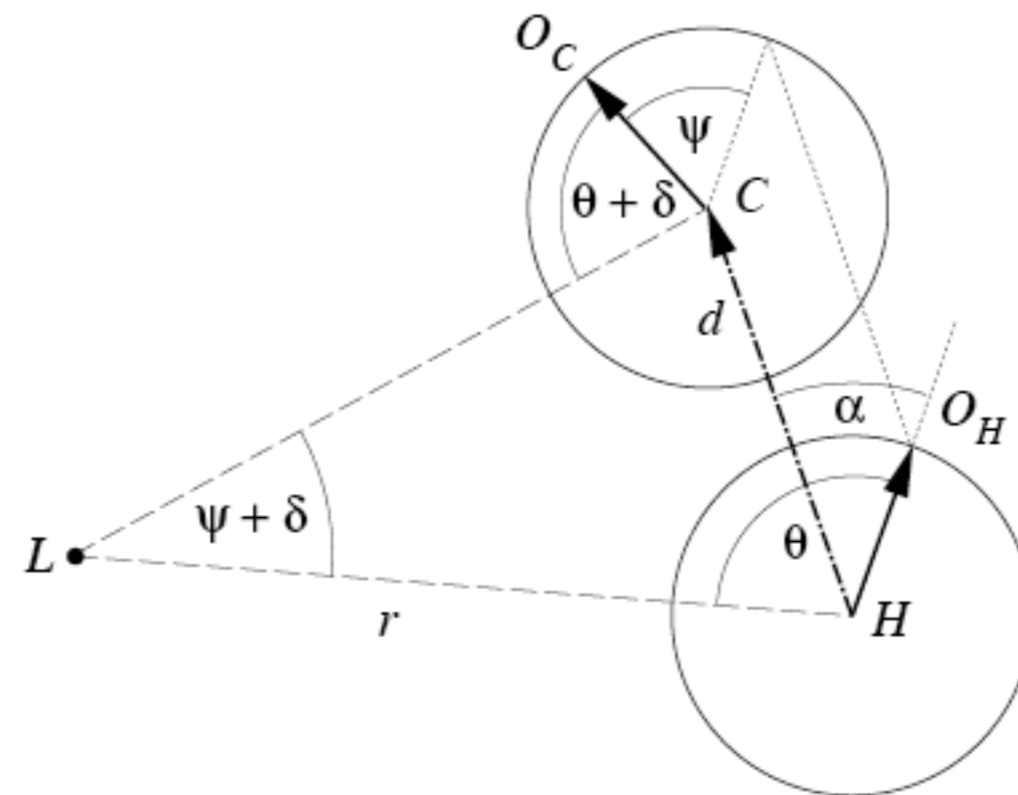


Warping

- Franz et al. (1998): Where did I take that snapshot? Scene-based homing by image matching, *Biological Cybernetics*, 97, 191–202
- lokales Homing-Verfahren basierend auf Bildverzerrung (Warping) entsprechend Bewegungsparametern
- Minimumssuche über Bewegungsparametern
- Besonderheit: keine Extraktion von "Landmarken"
- kein Kompass erforderlich
- sehr robustes Verfahren



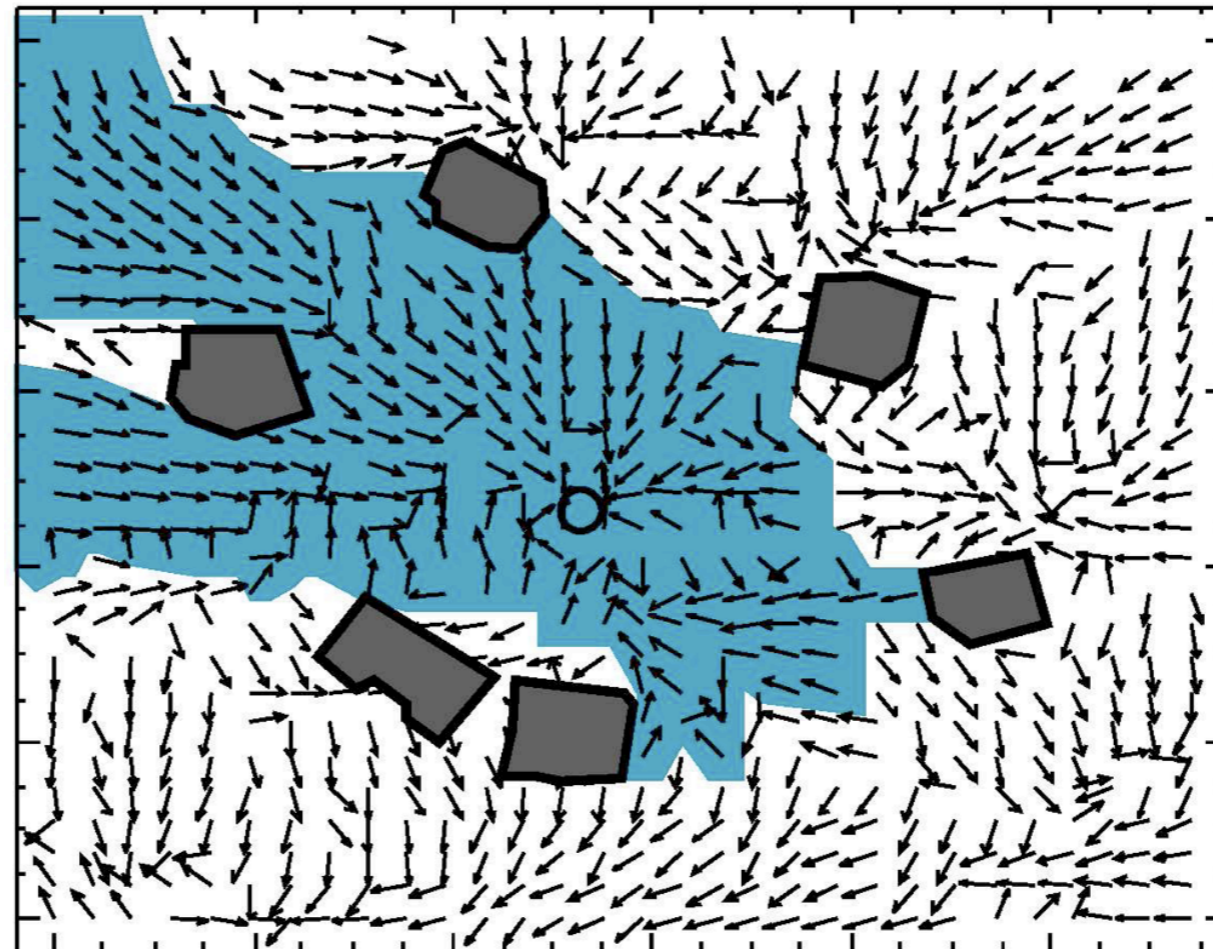
Image Warping



(Franz et al.)



Catchment Area

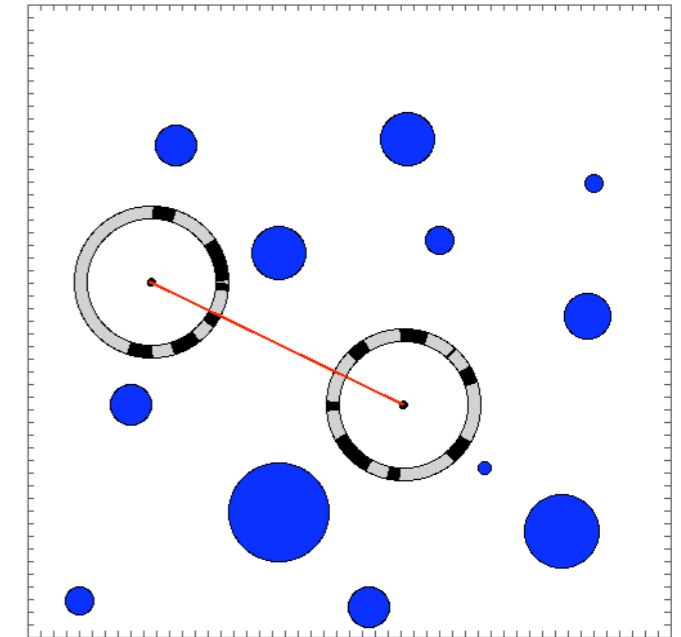
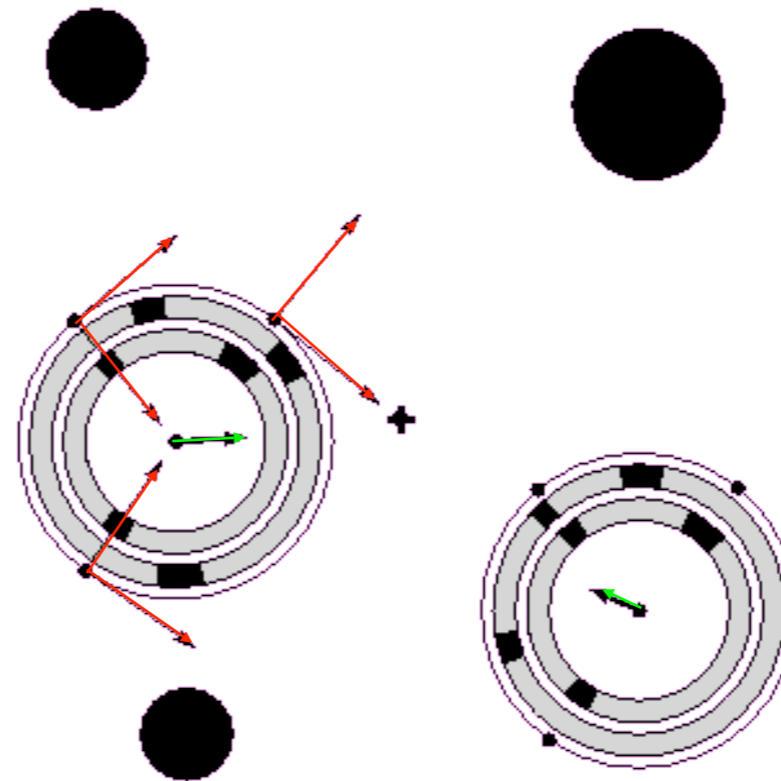


(Franz et al.)



Schnappschuss Modell

- home snapshot
- aktueller snapshot
- home Vektor
Berechnung durch
Vergleich

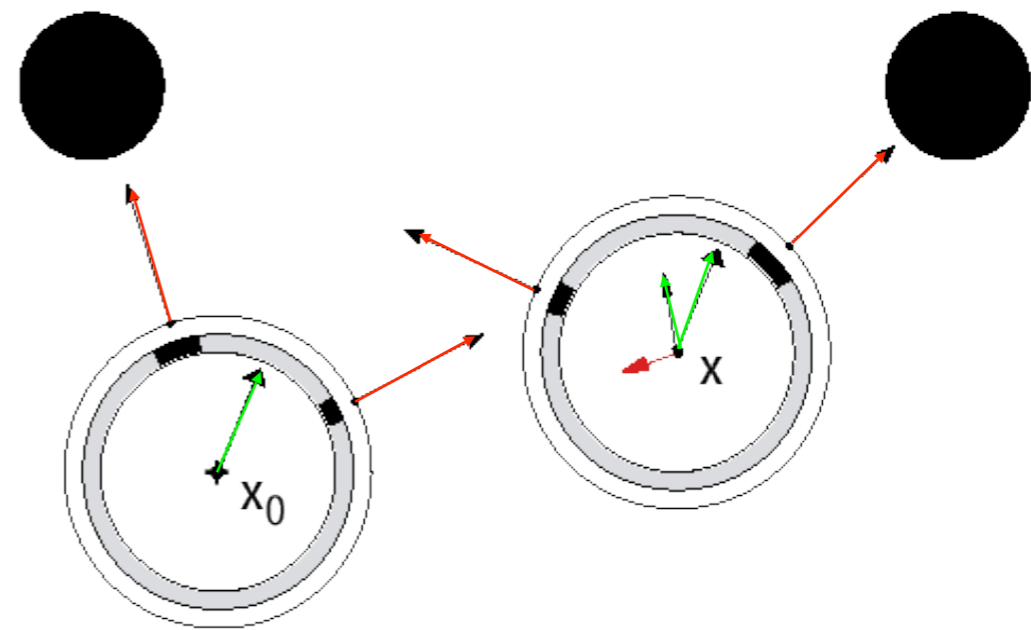


(Cartwright and Collett, 1983)



ALV Modell

- nur ein Vektor muss gespeichert werden
- Average Landmark Vektor
- effizientes Verfahren
- Resultate ähnlich zum snapshot Modell

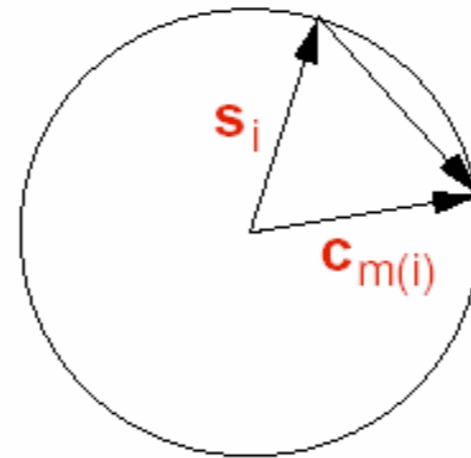


(Lambrinos et al., 2000)



ALV Modell

Herleitung ALV-Modell



- Differenzvektor-Modell:

$$\mathbf{h} = \sum_i (\mathbf{c}_{m(i)} - \mathbf{s}_i)$$

- Annahme: perfektes Matching:

$$m(i) = i$$

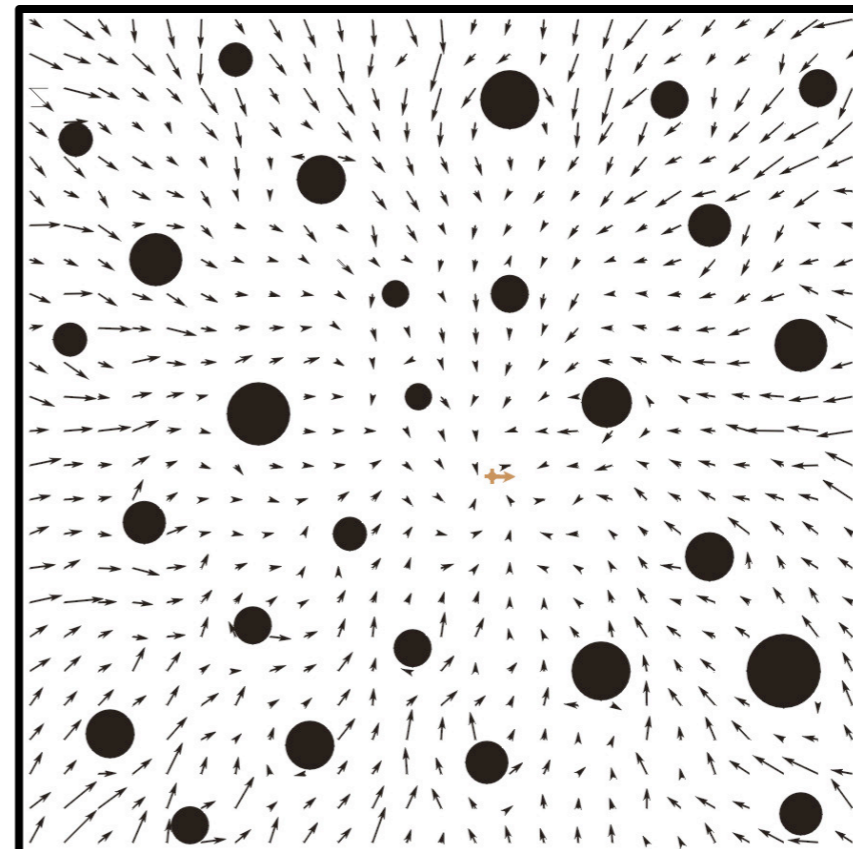
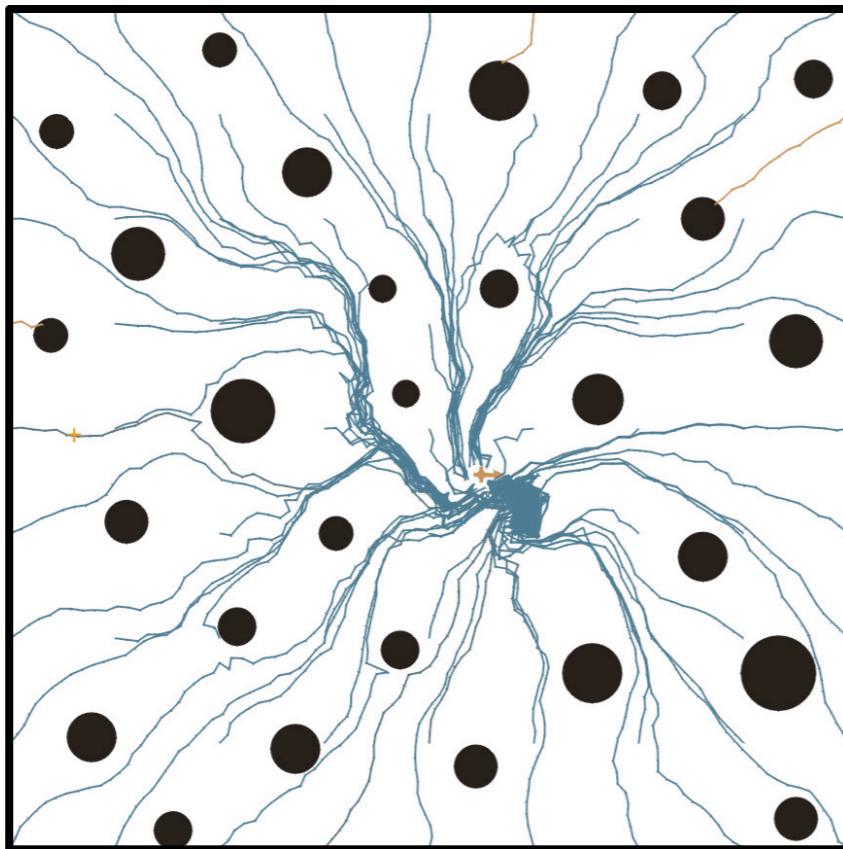
- Vereinfachung:

$$\mathbf{h} = \sum_i (\mathbf{c}_i - \mathbf{s}_i) = \sum_i \mathbf{c}_i - \sum_i \mathbf{s}_i$$

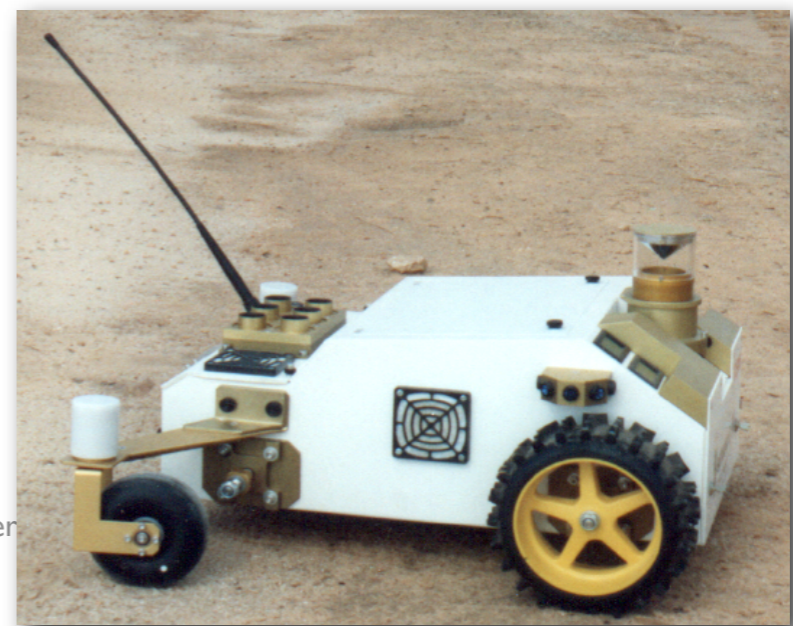
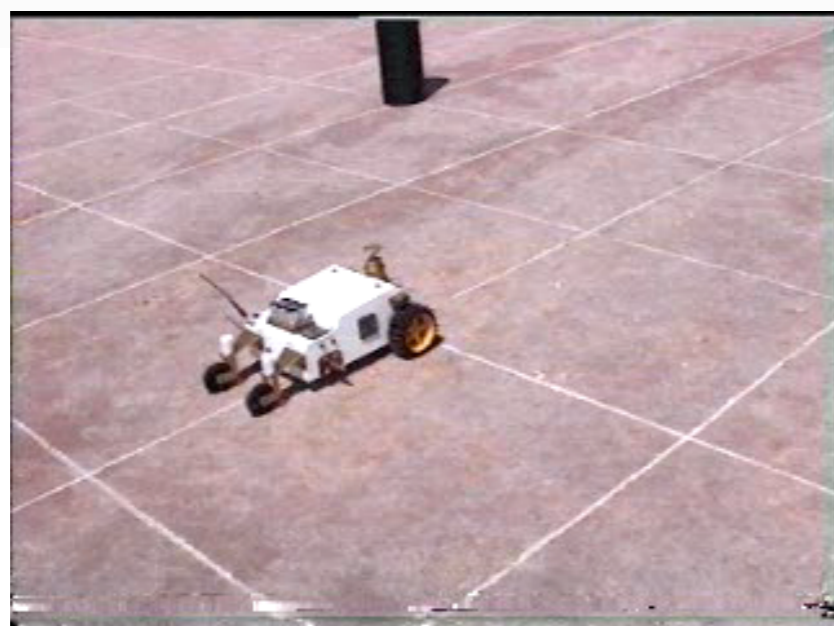
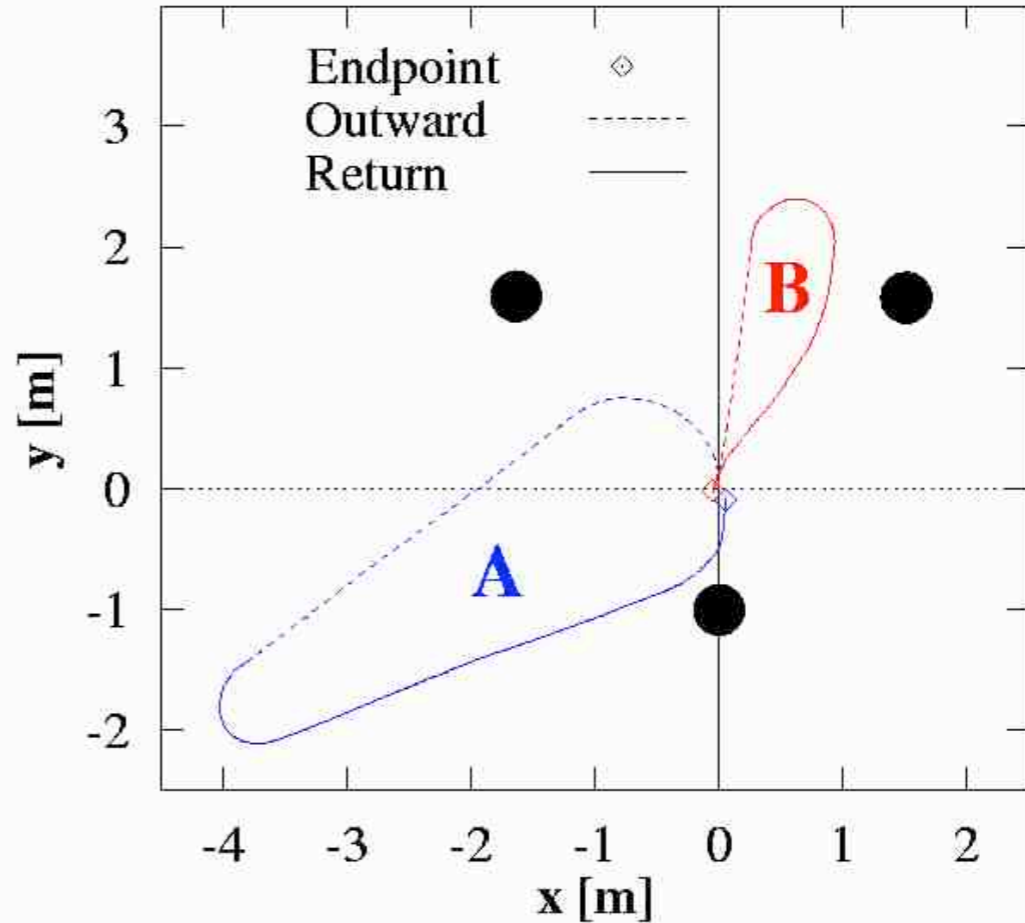
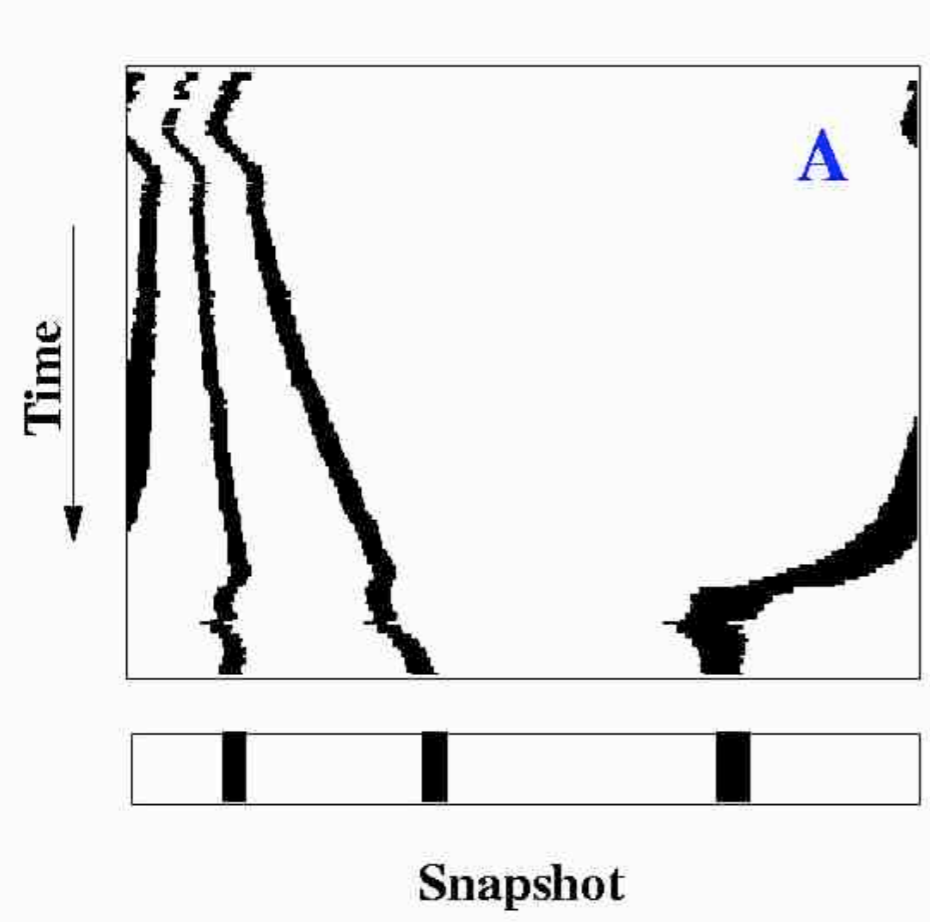


ALV Modell

- Simulationsergebnisse



Sahabot II mit Schnappschuss Model



Polarisiertes Licht

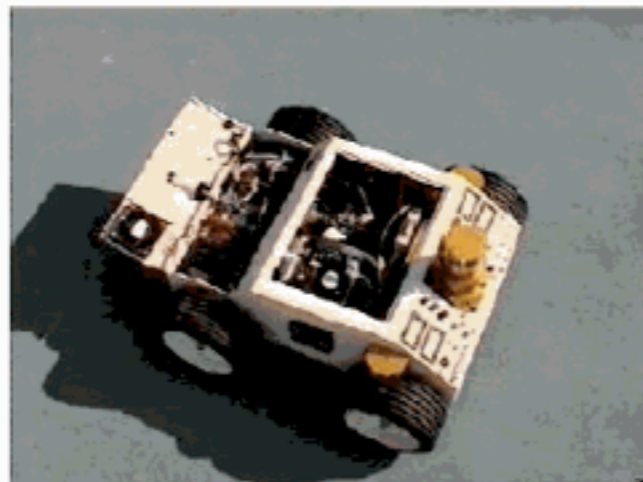
Kompass, Sahabot II



panoramic camera



Polarisations-Sensoren



Blick in Sahabot 2



Umgebungslicht-Sensoren



POL Kompass

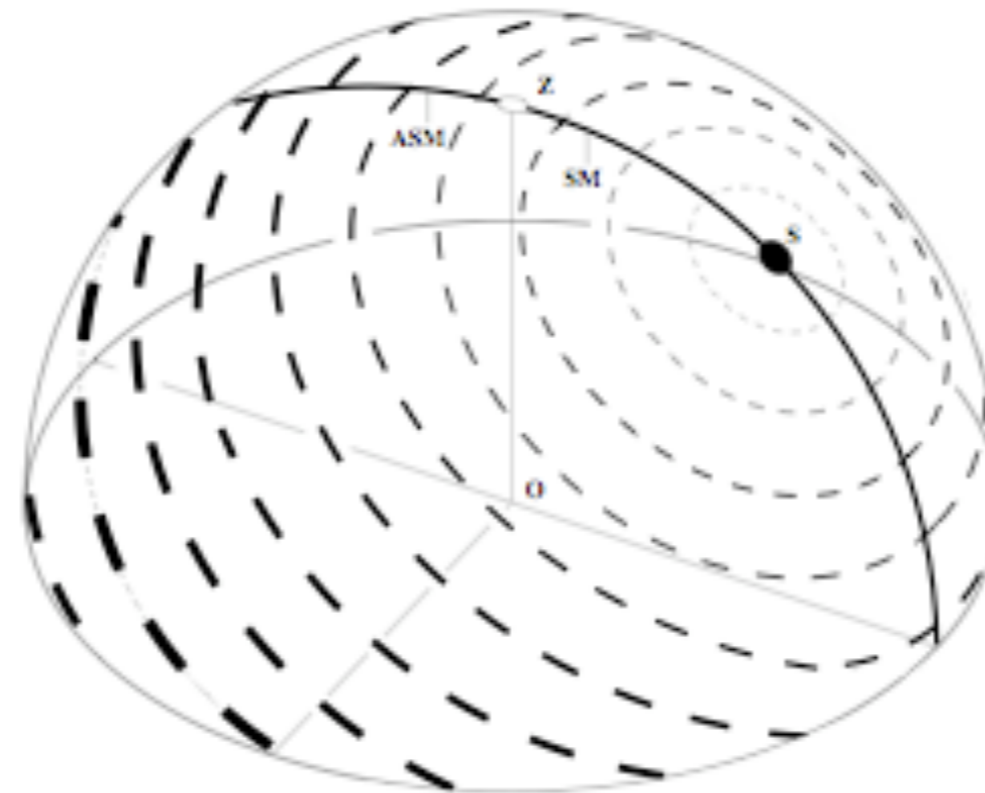


Fig. 2. 3-D representation of the pattern of polarization in the sky as experienced by an observer in point O. Orientation and width of the bars depict the direction and degree of polarization, respectively. A prominent property of the pattern is a symmetry line running through sun (S) and zenith (Z), called “solar meridian” (SM) on the side of the sun and “anti-solar meridian” (ASM) on the opposite side. (Adapted from [46].)



POL Kompass

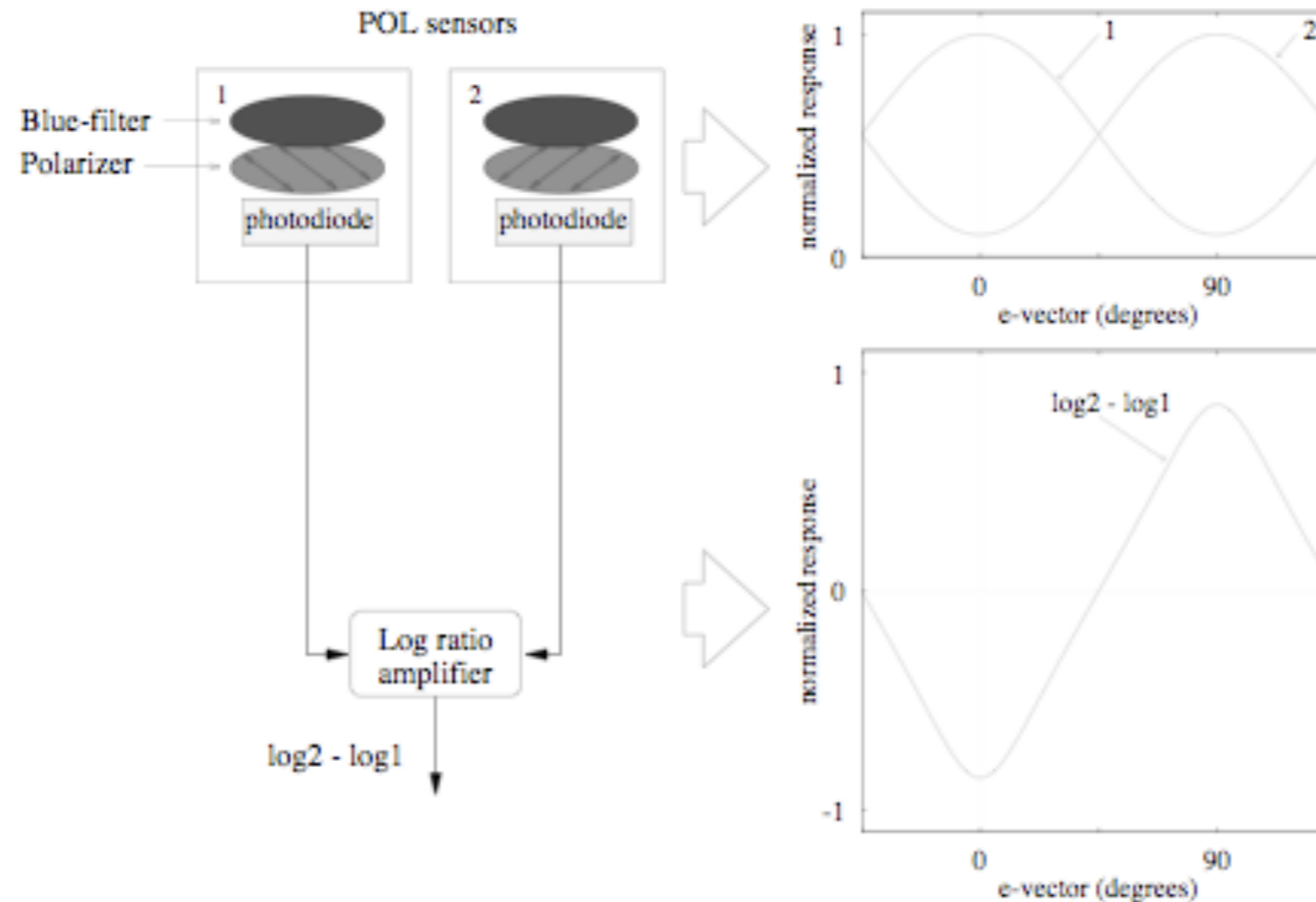
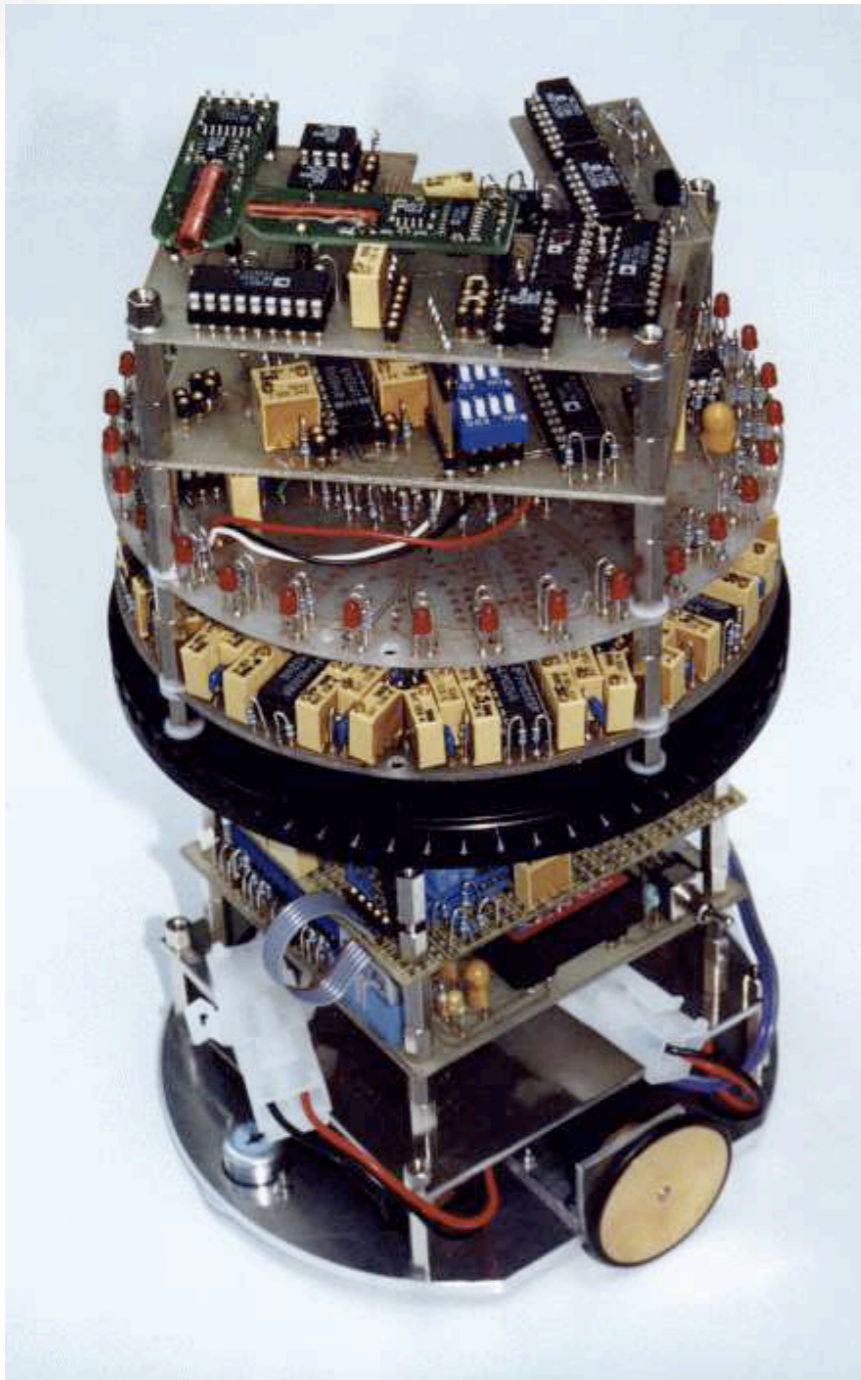


Fig. 4. Diagrammatic description of a polarization-opponent unit (POL-OP unit). A POL-OP unit consists of a pair of POL-sensors and a log-ratio amplifier. The log-ratio amplifier receives input from the two POL-sensors and delivers the difference of their logarithmized signals. The e-vector responses of the POL-sensors (1, 2) follow a \cos^2 -function.



Analog Robot mit ALV



- Kompass-Einheit
- AL-Vektor-Berechnung
- Kantenfilter
- 32 Photodioden im Ring
- Motorsteuerung

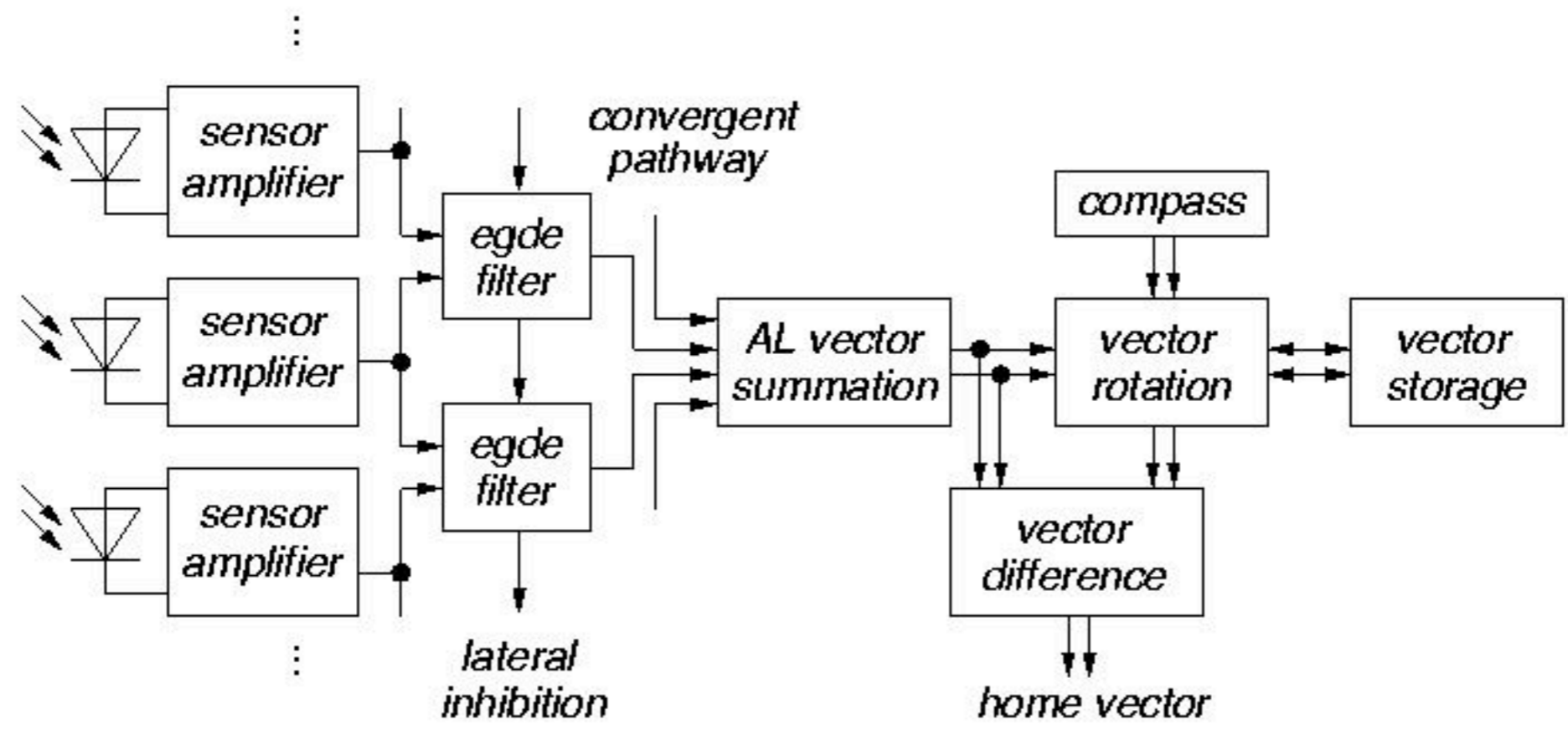
91 Operationsverstärker
(1 OPV = 1 Neuron)

64 of 91: Landmarken-Detektion

12 Multiplizierer (Kompass)

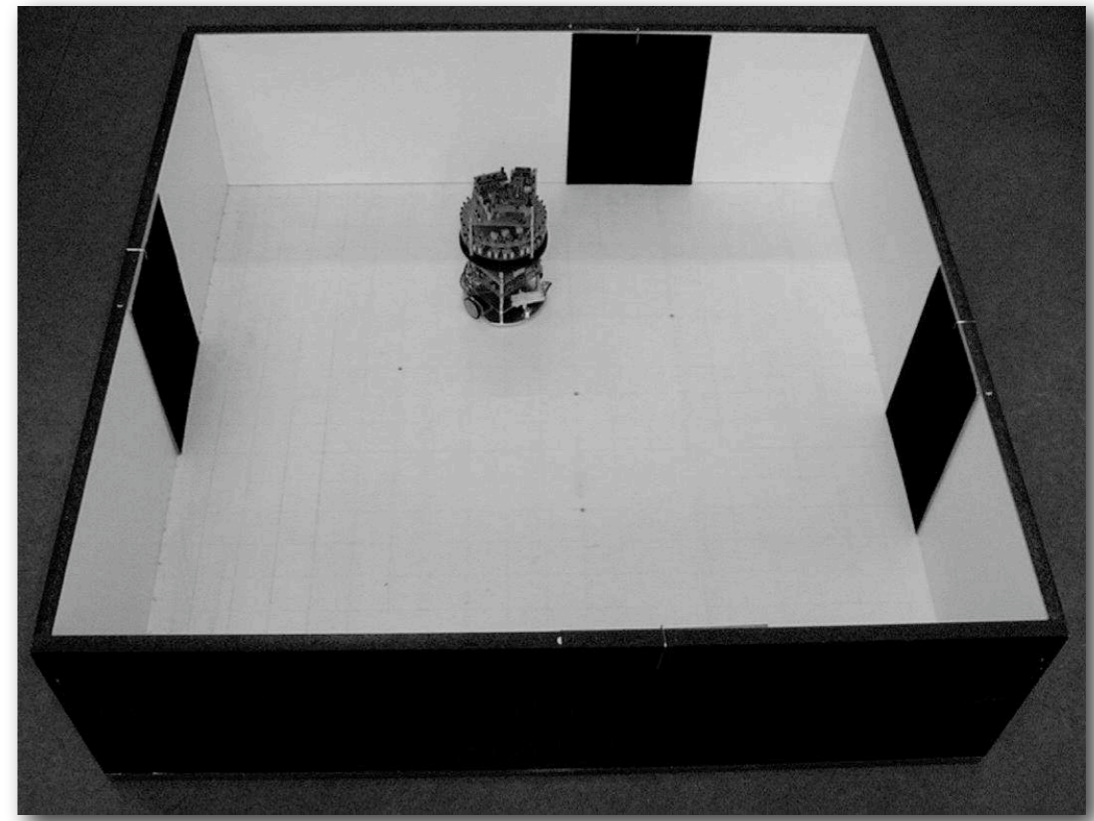
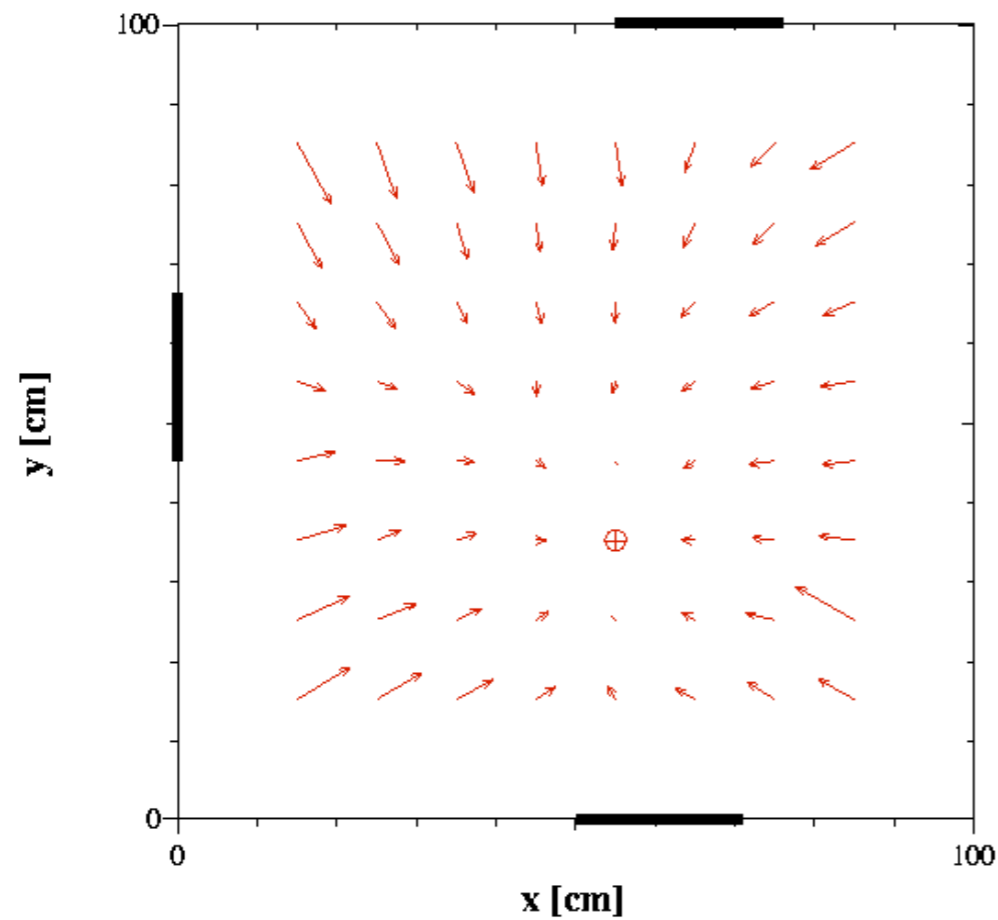


Analog Robot

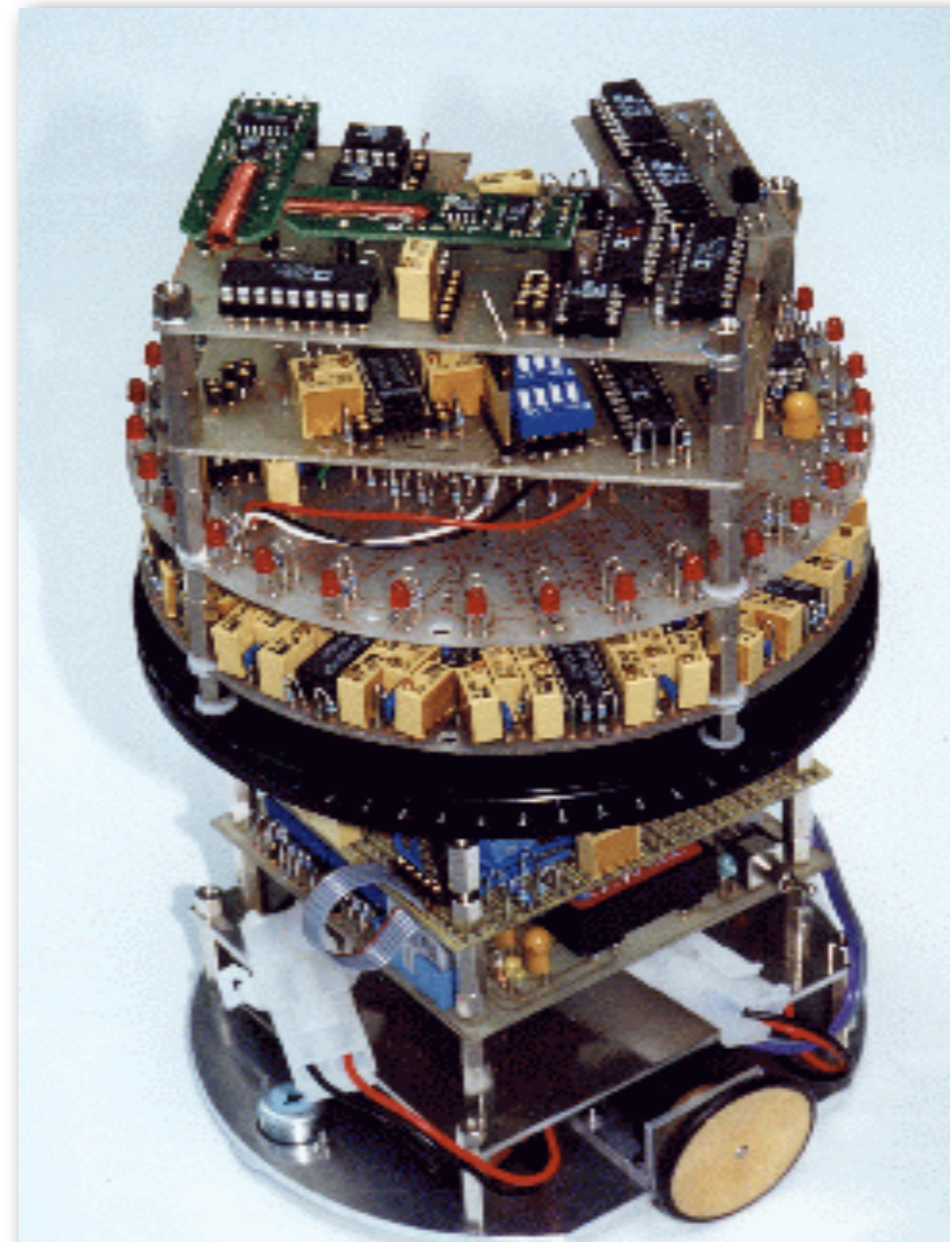
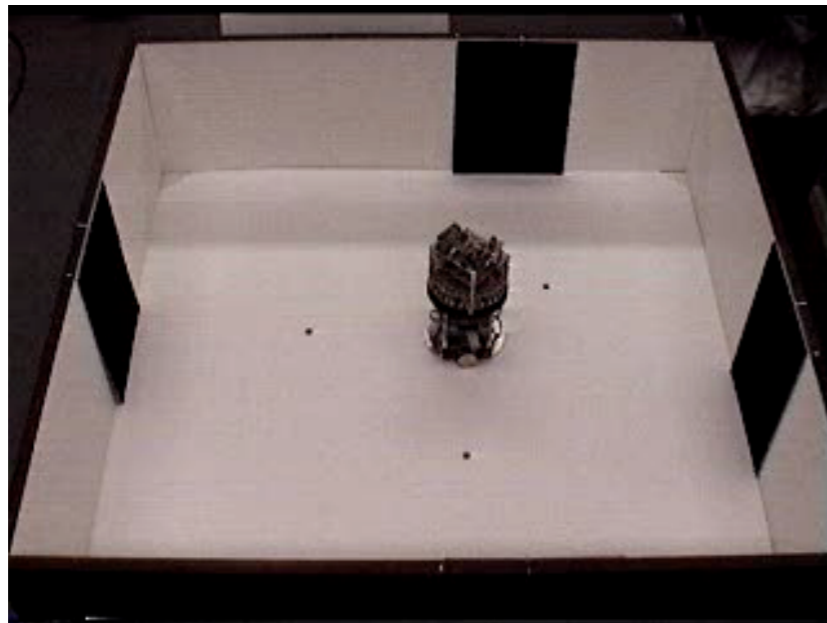


Szenario

home vectors, 3 landmarks



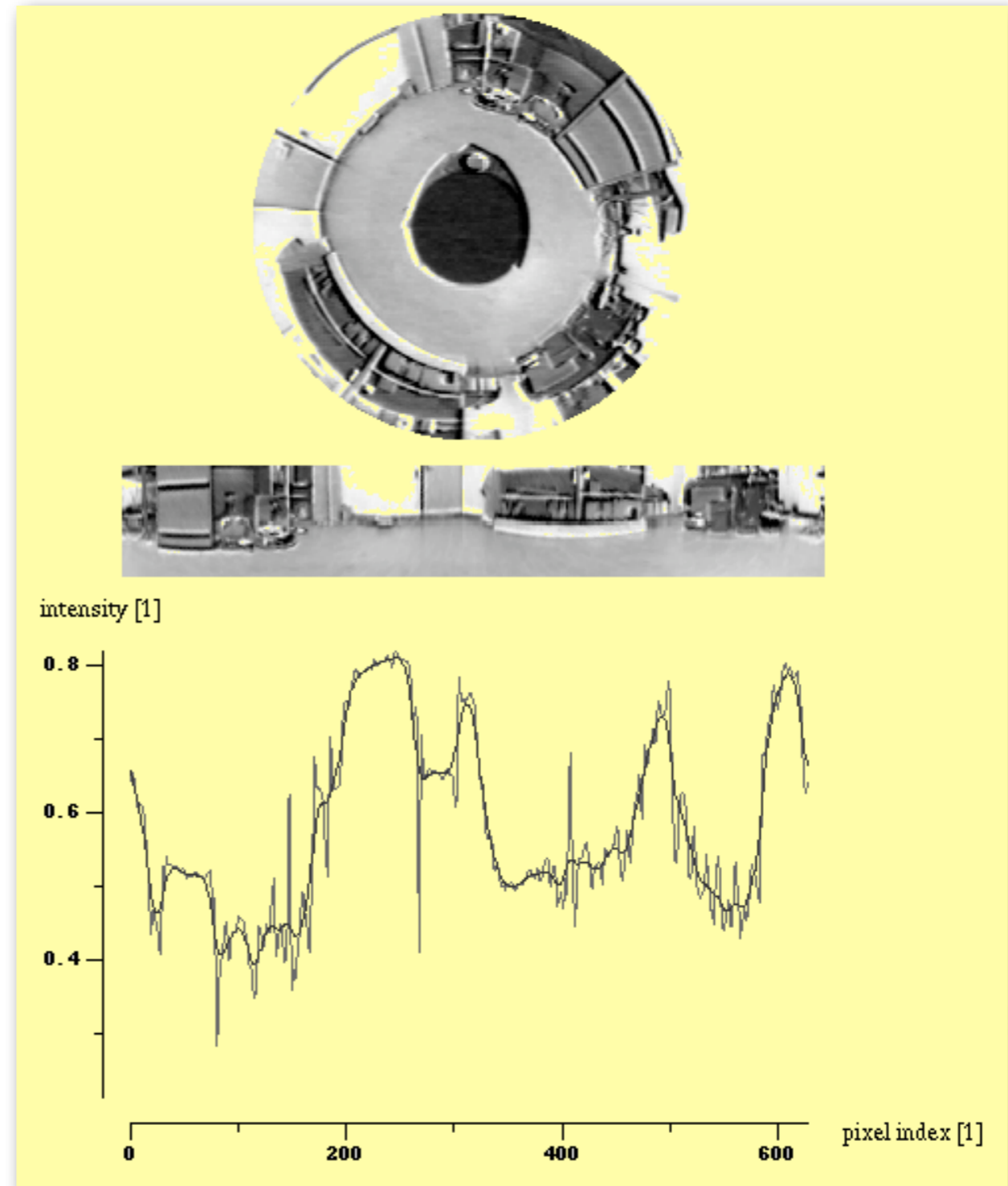
Analog Roboter mit ALV Modell



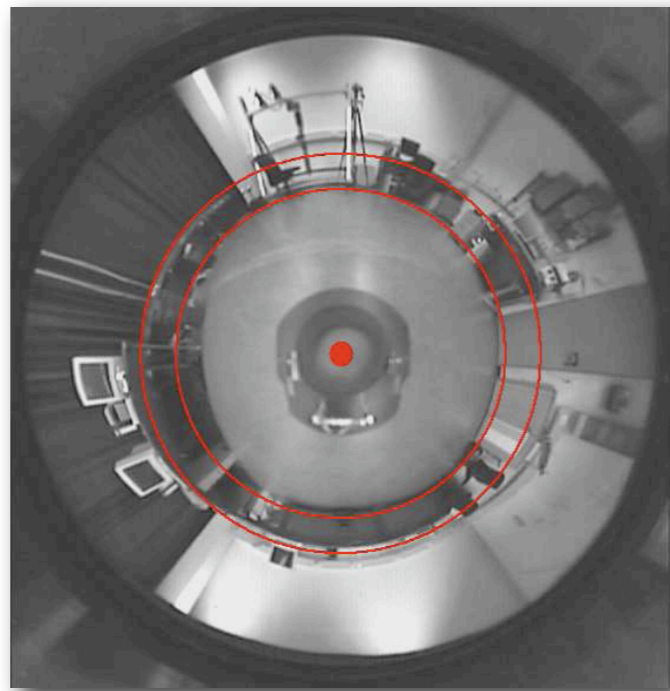
Analog Roboter by Ralf Möller,
AI Lab Zurich



Roboter mit Omni-Cam



Omnidirektionale Kamera



Horizontale Verarbeitung



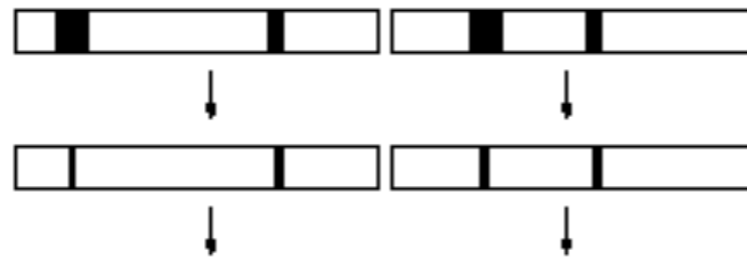
2D Visuelles Matching



- (A. Vardy)

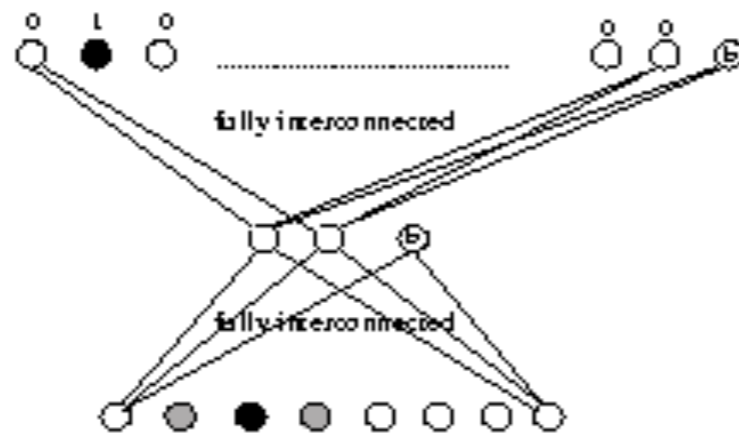


Lernszenario



current and goal view

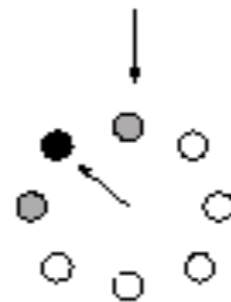
filtered views



input layer

hidden layer

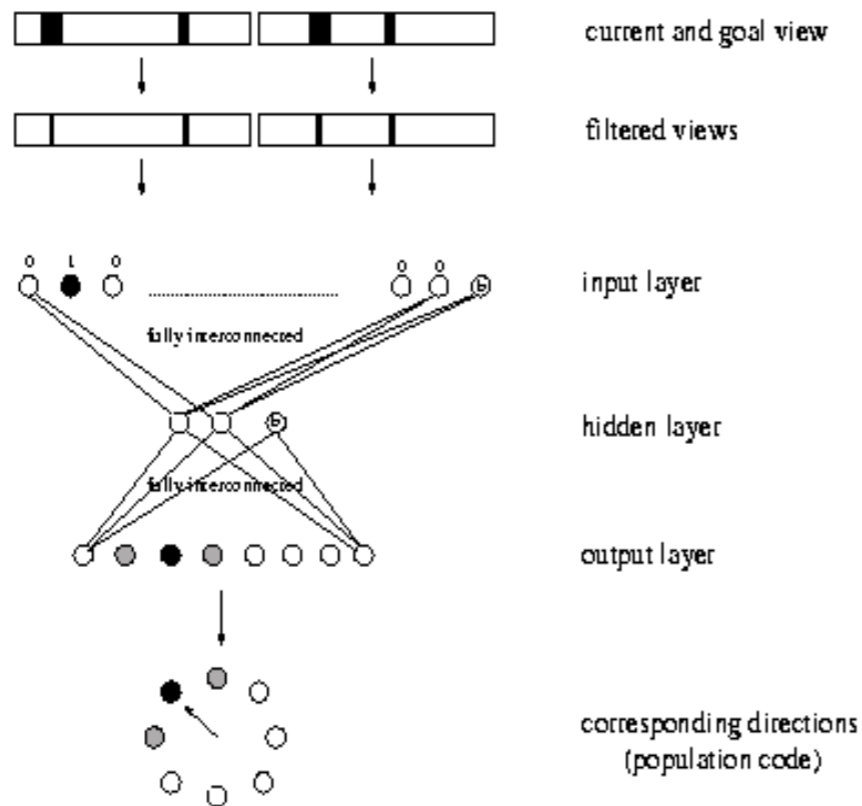
output layer



corresponding directions
(population code)



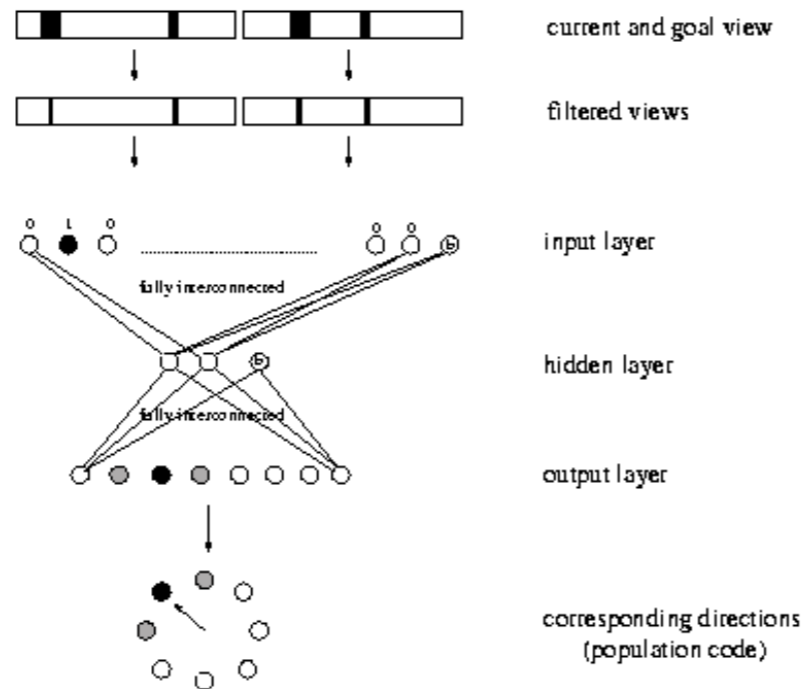
Lernszenario



Multi-Layer Perzeptron mit Backpropagation



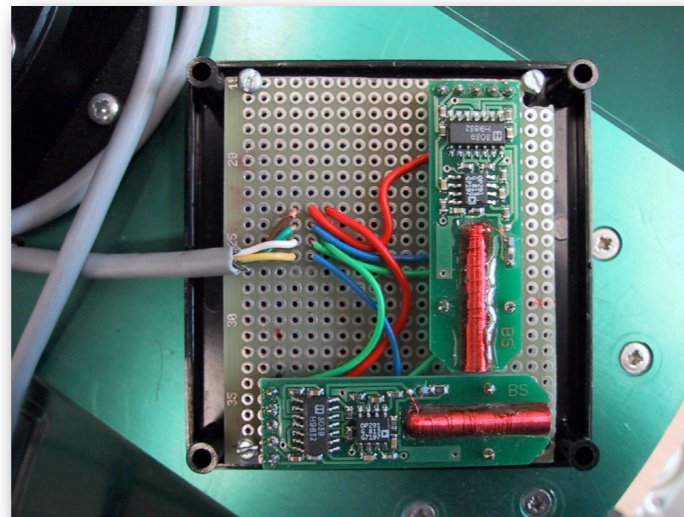
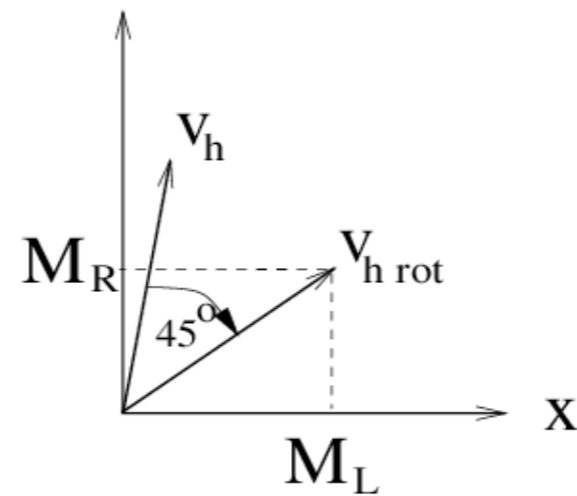
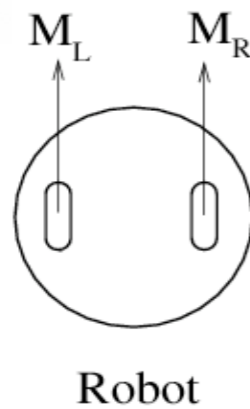
Lernszenario



Population Coding (Winkel/Orientierung)



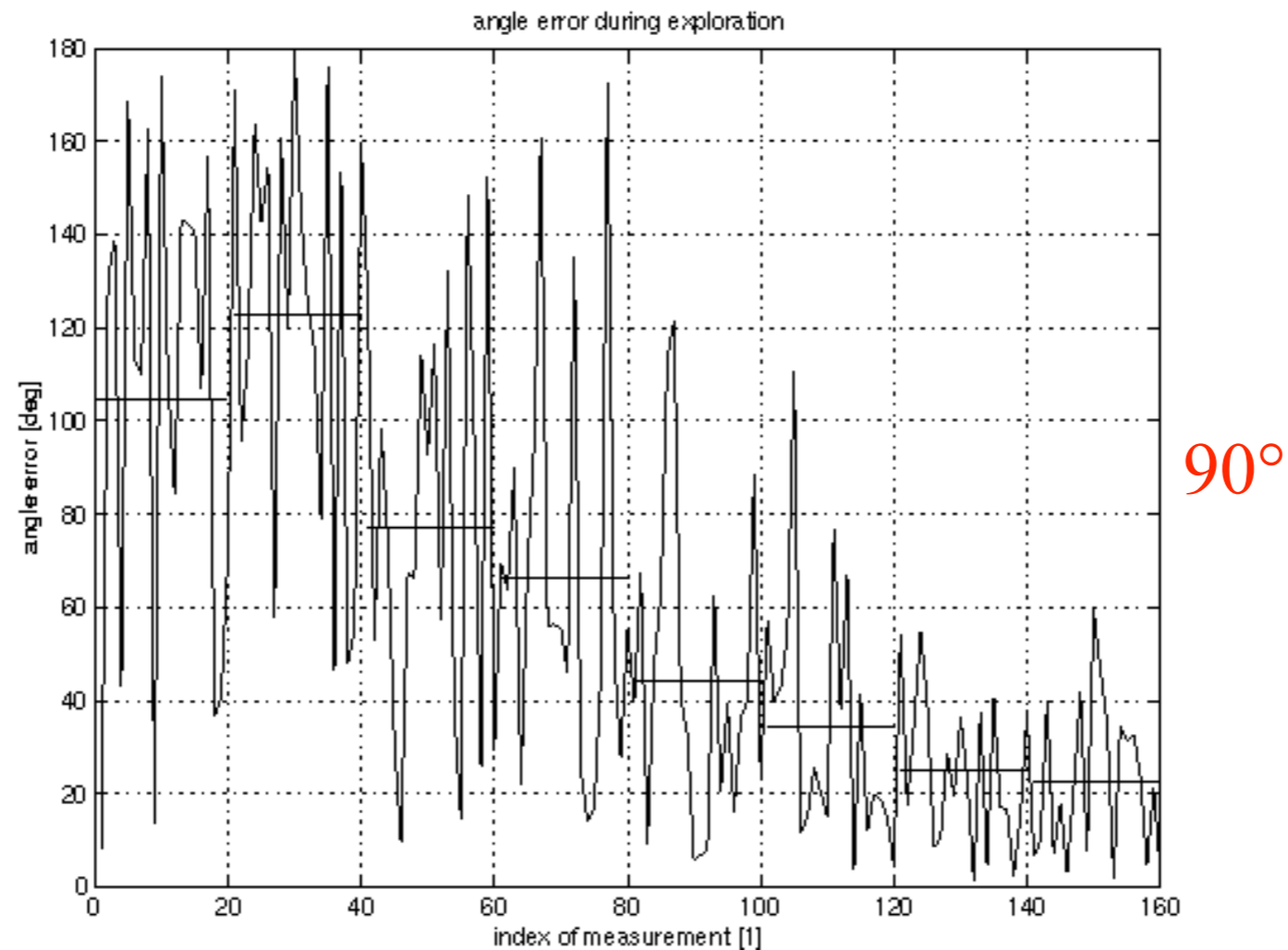
Lernszenario



Fluxgate Kompass



Visuelles Homing ist lernbar

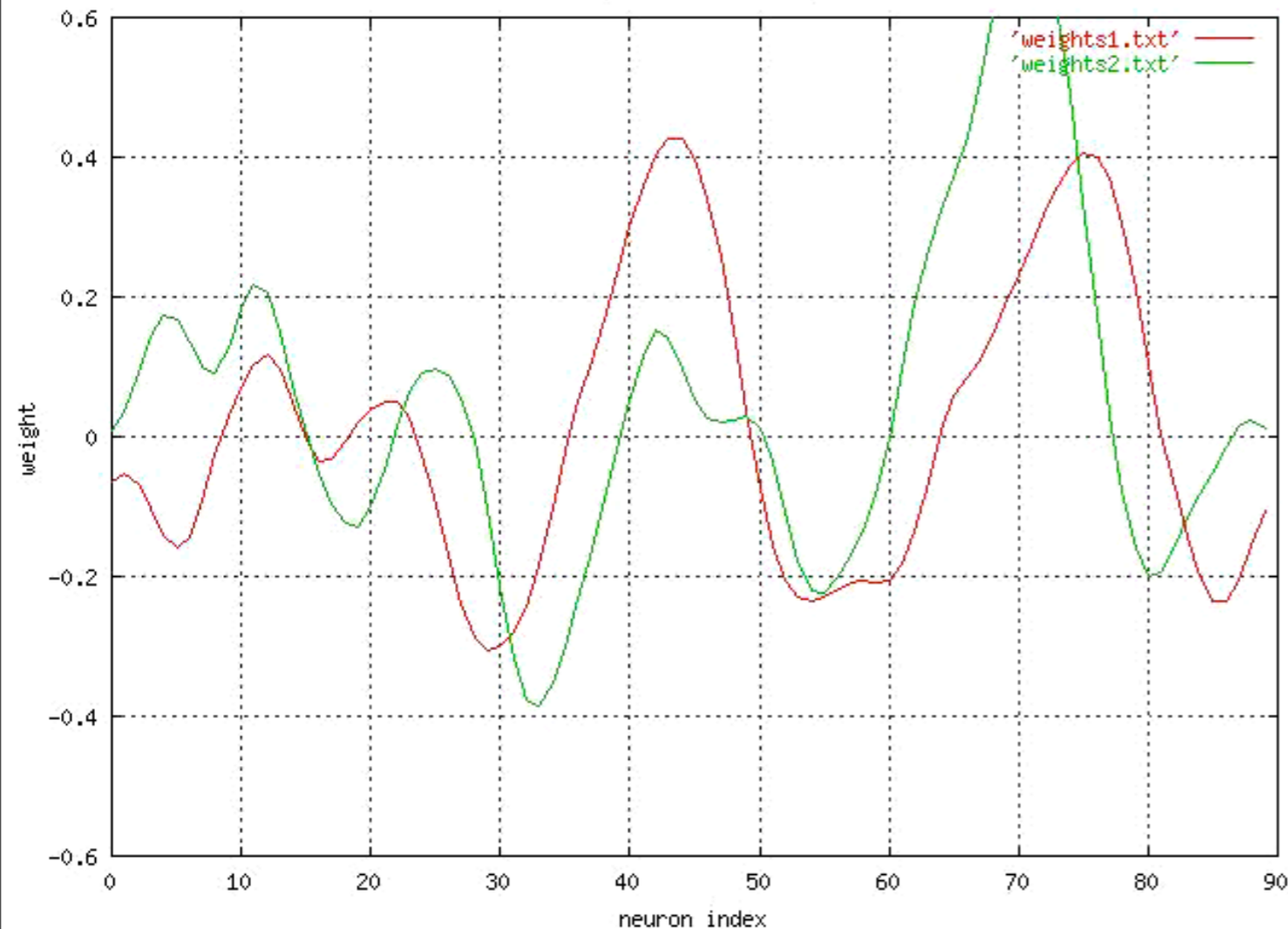


Winkelfehler des Home Vektors



Das gelernte Modell entspricht dem ALV Modell

Hebbian Learning with samcam snapshots: s1-s2

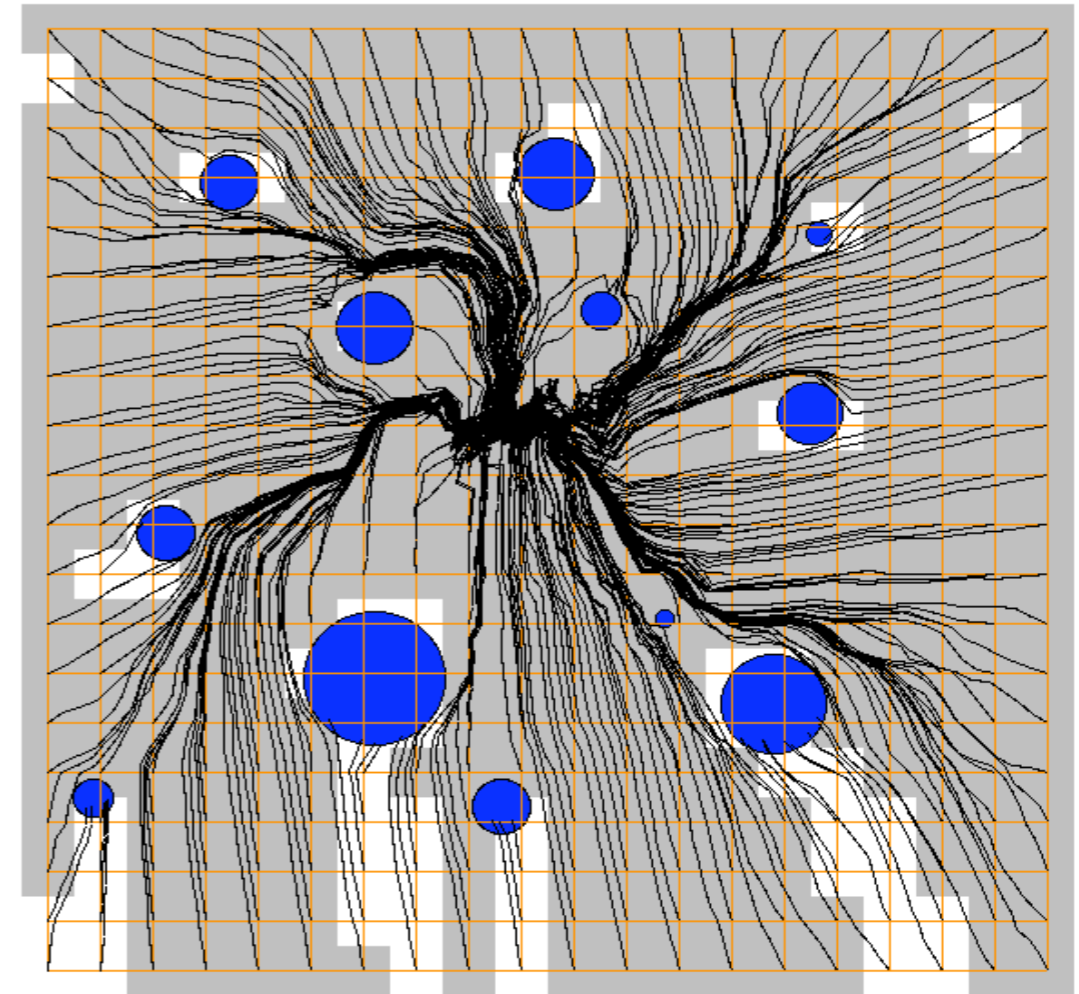
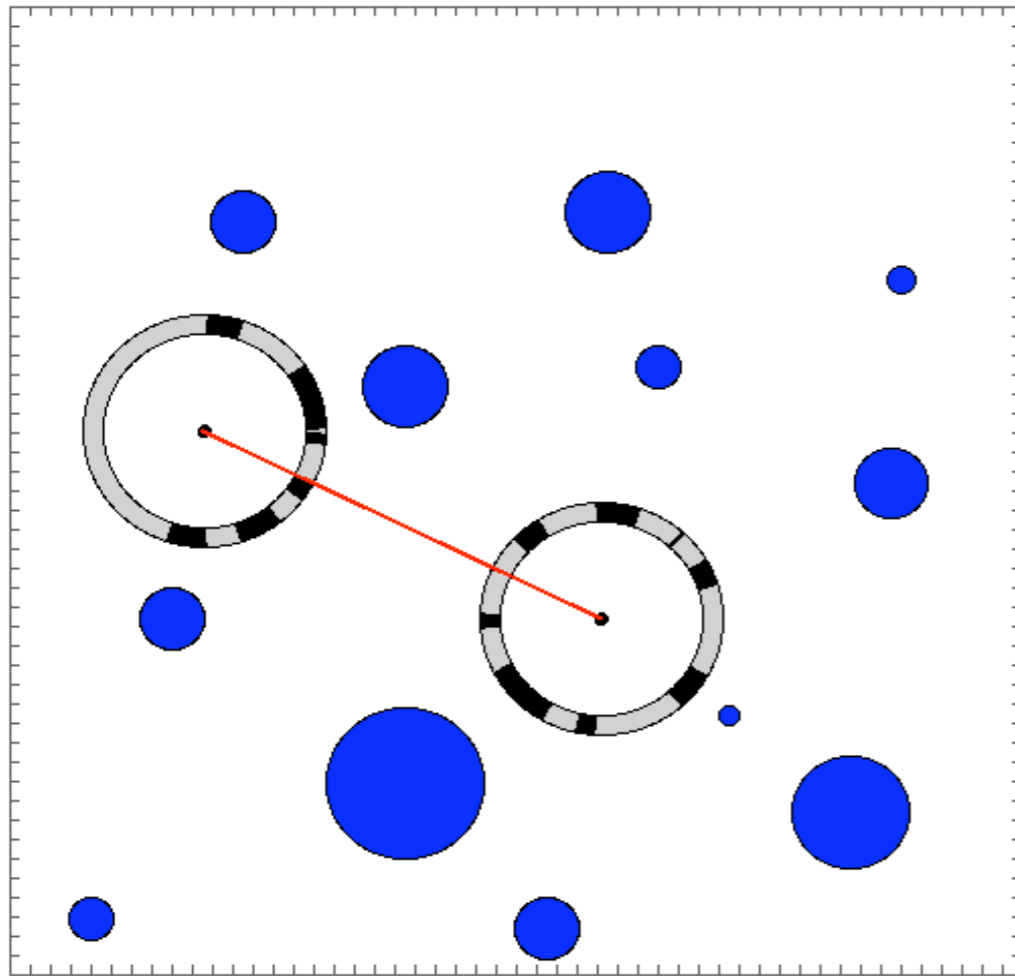


$$\begin{aligned}
 v_h &= (x, y) \\
 &= \left(\sum_{i=0}^{l-1} w_{ix} n_i, \sum_{i=0}^{l-1} w_{iy} n_i \right) \\
 &= C \left(\sum_{i=0}^{l-1} \cos(g_i) n_i, \sum_{i=0}^{l-1} \sin(g_i) n_i \right) \\
 &= C ALV_n \\
 &= C (ALV_{s_1} - ALV_{s_2})
 \end{aligned}$$

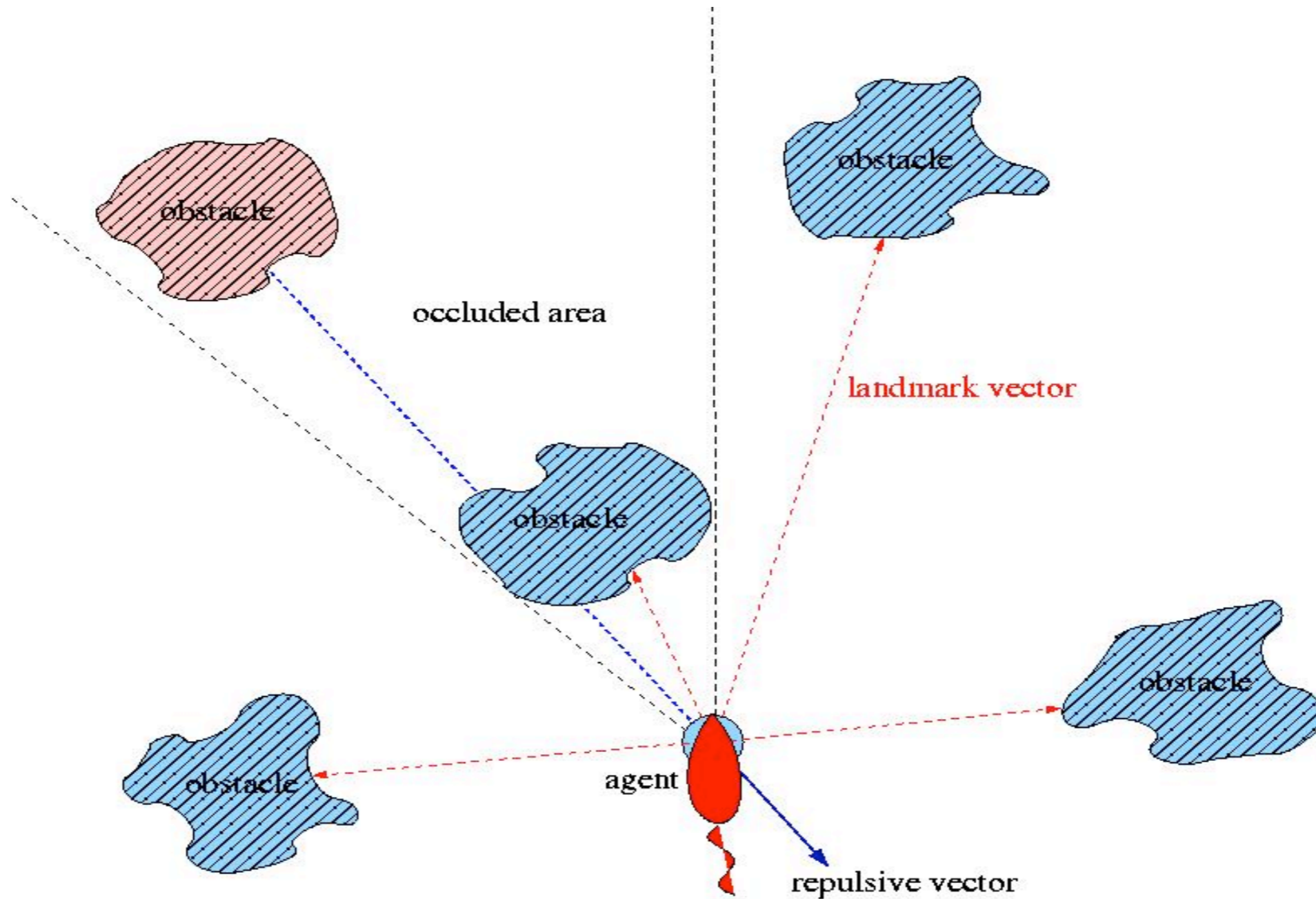
Gewichte zwischen visueller und Motor Schicht



Emergente Hindernis-Vermeidung

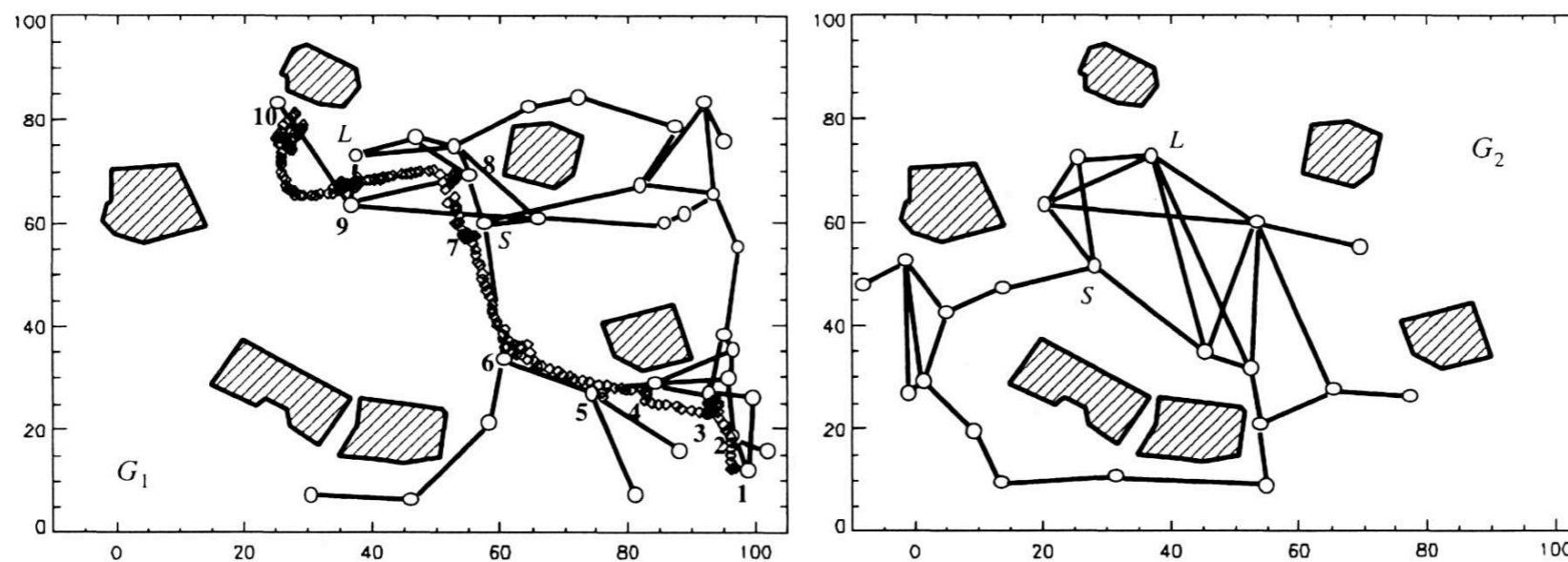


Einfache Erklärung



Topologische Karten

- moderner Ansatz in der Robotik
- Karte = Menge von Orten (nur "interessante" Orte)
- Navigation = Bestimmung eines Weges zum Ziel
- "Wie komme ich heim?"



(Franz et al.)



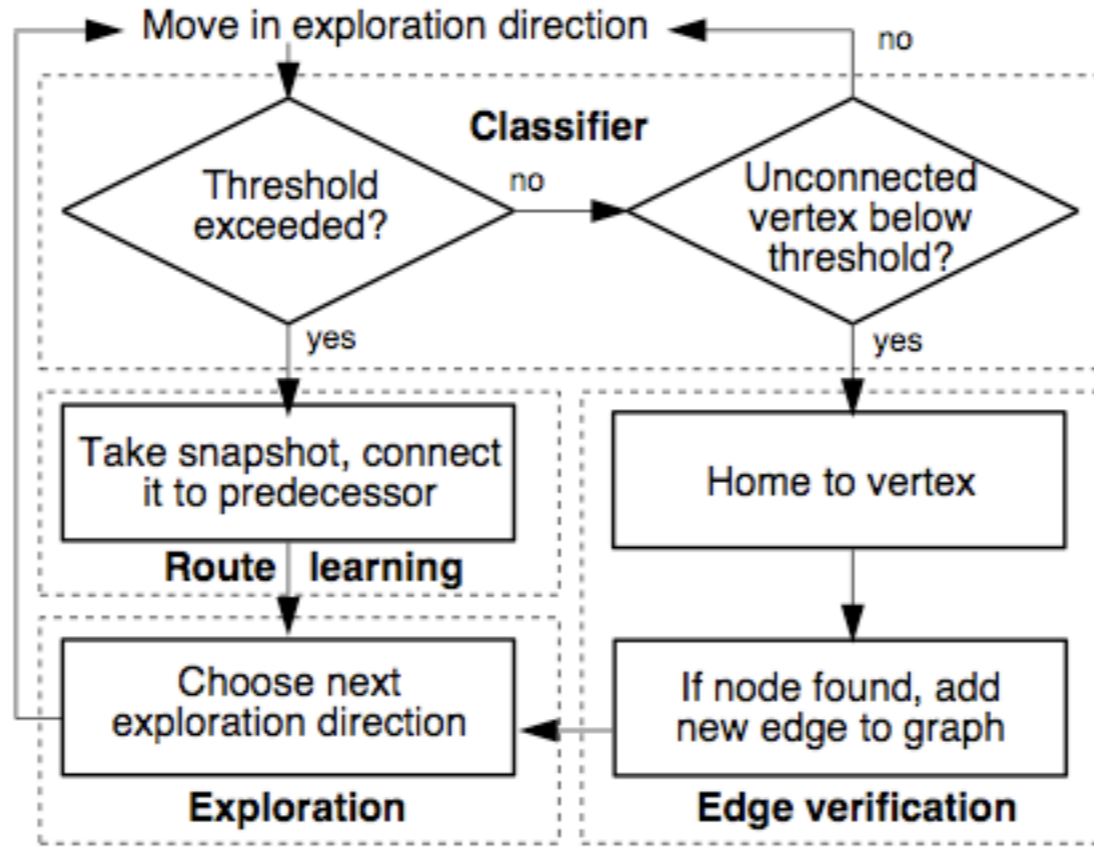
Learning View Graphs

- Franz et al. (1998):

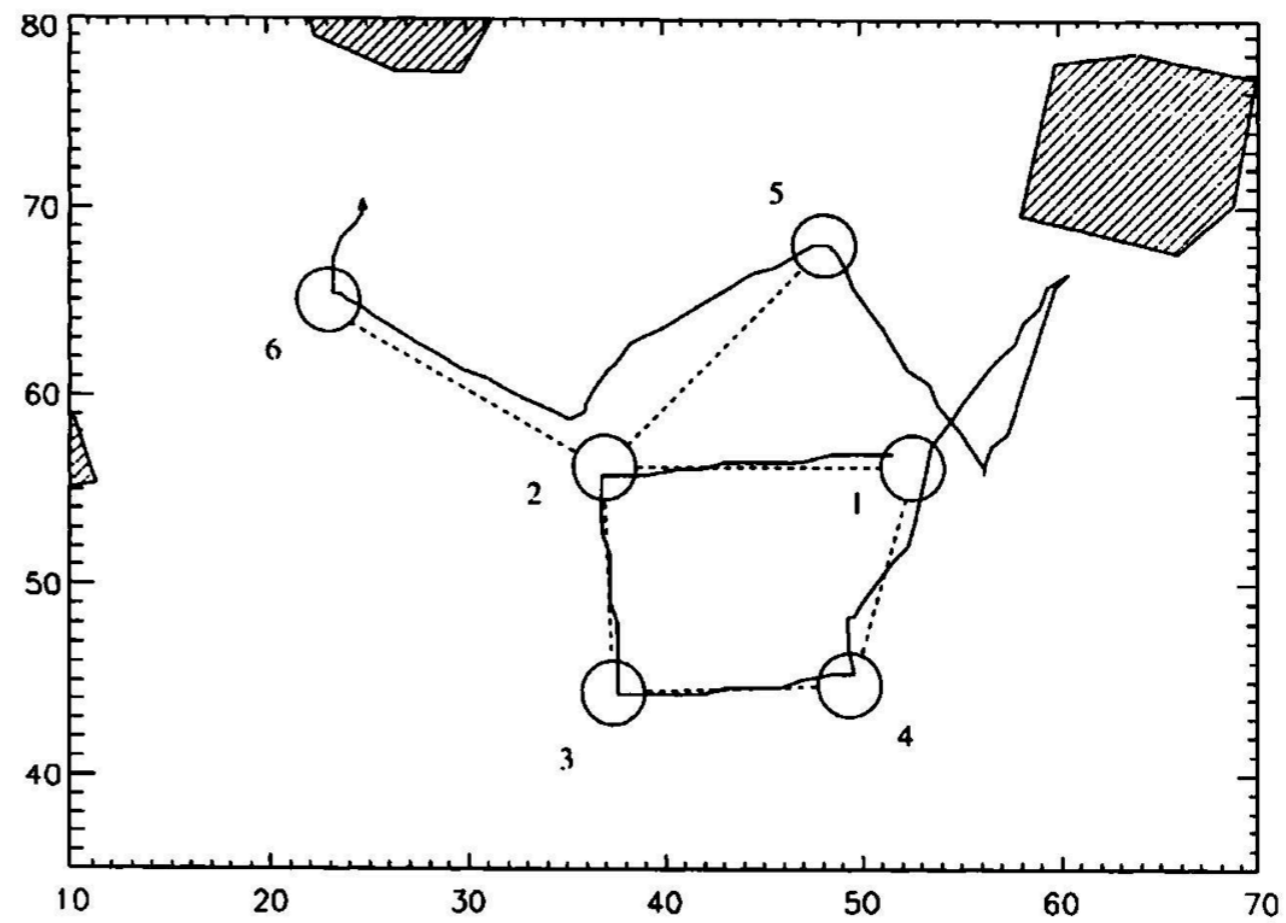
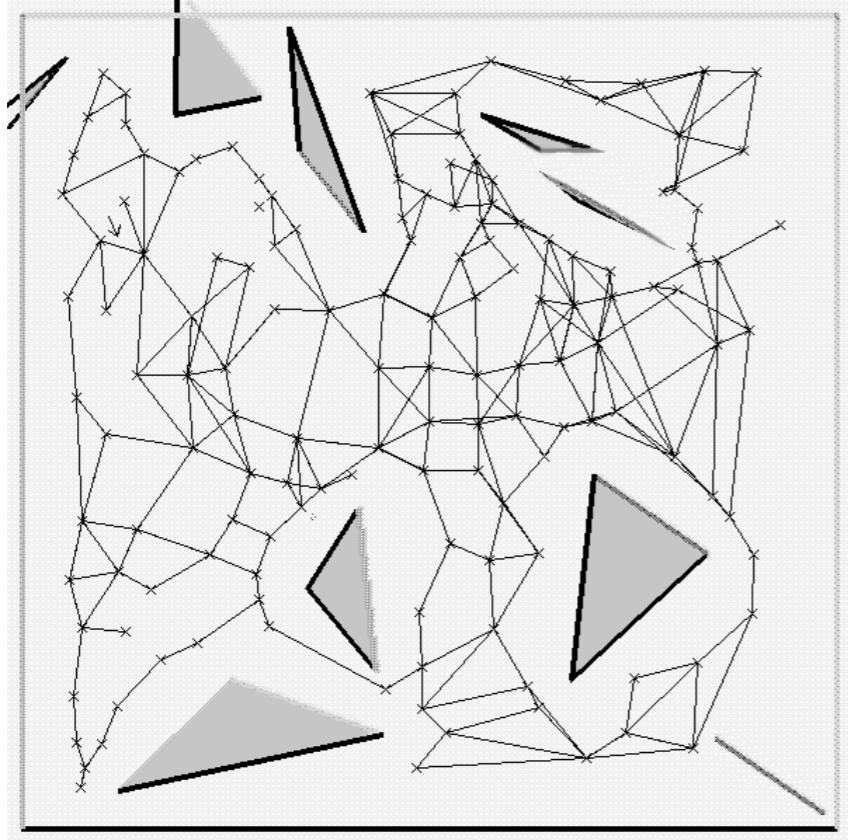
Learning View Graphs for Robot
Navigation, *Autonomous
Robots*, 5, 111–125



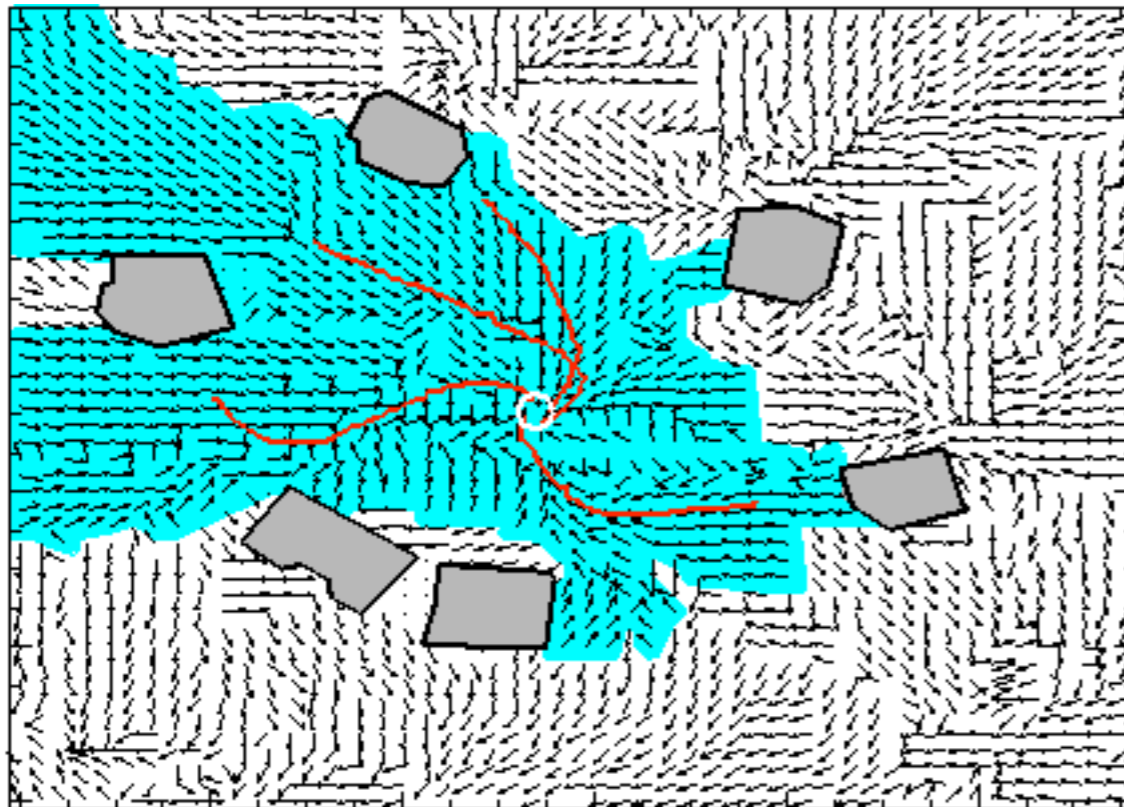
Learning View Graphs



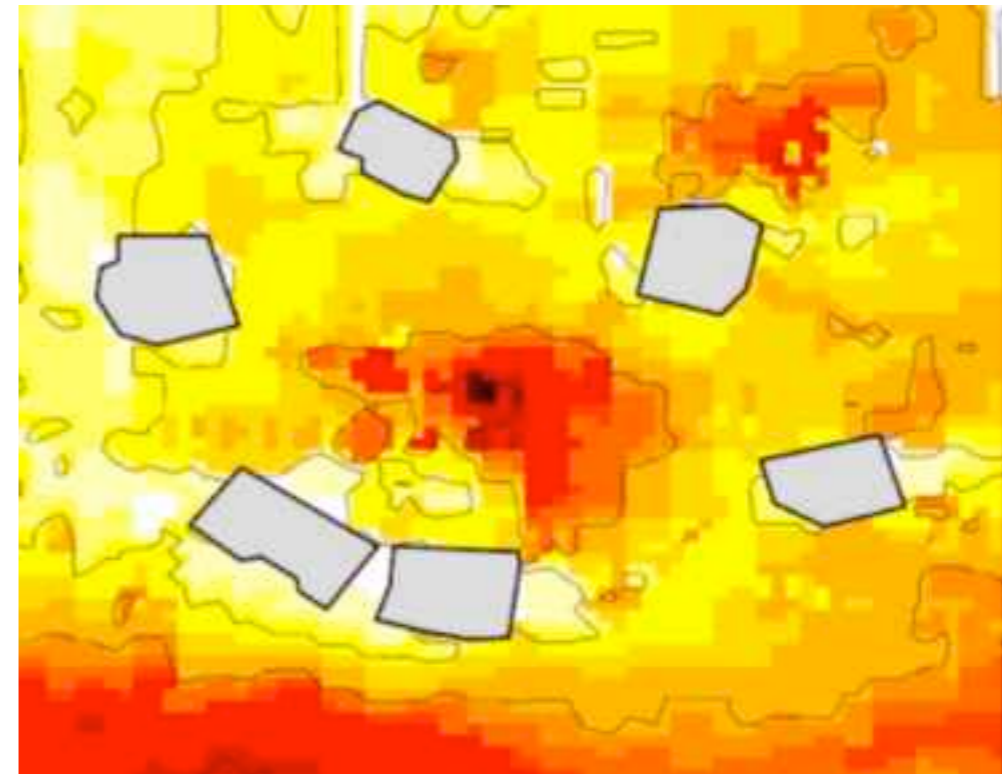
Learning View Graphs



catchment areas



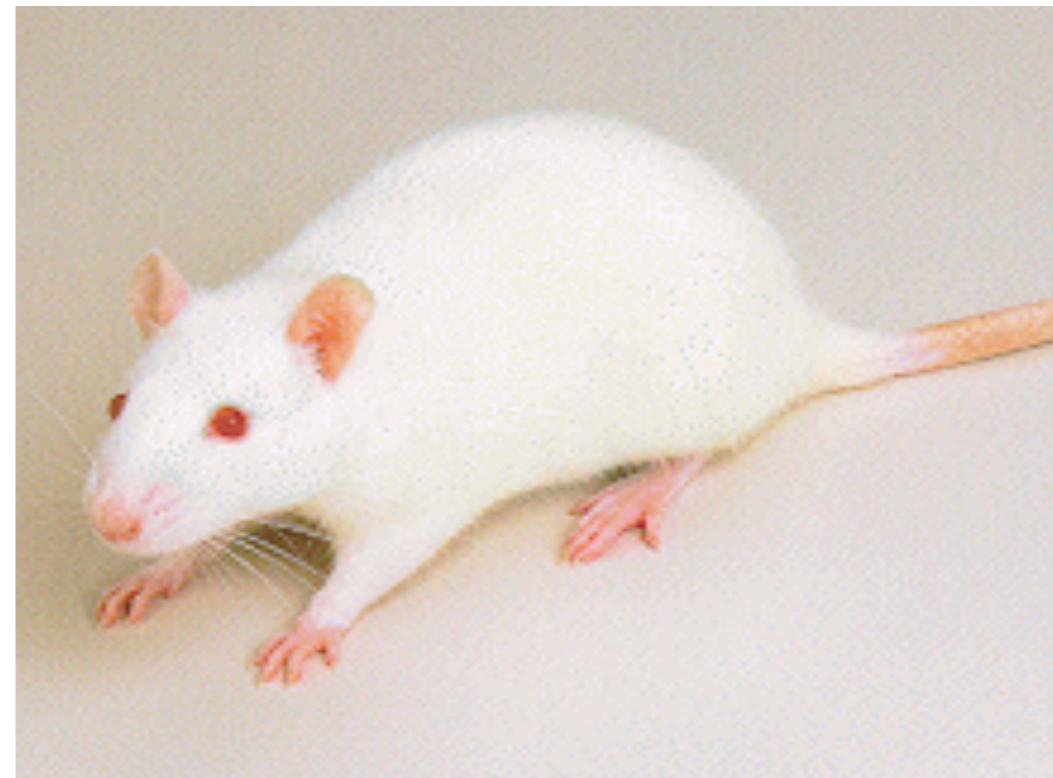
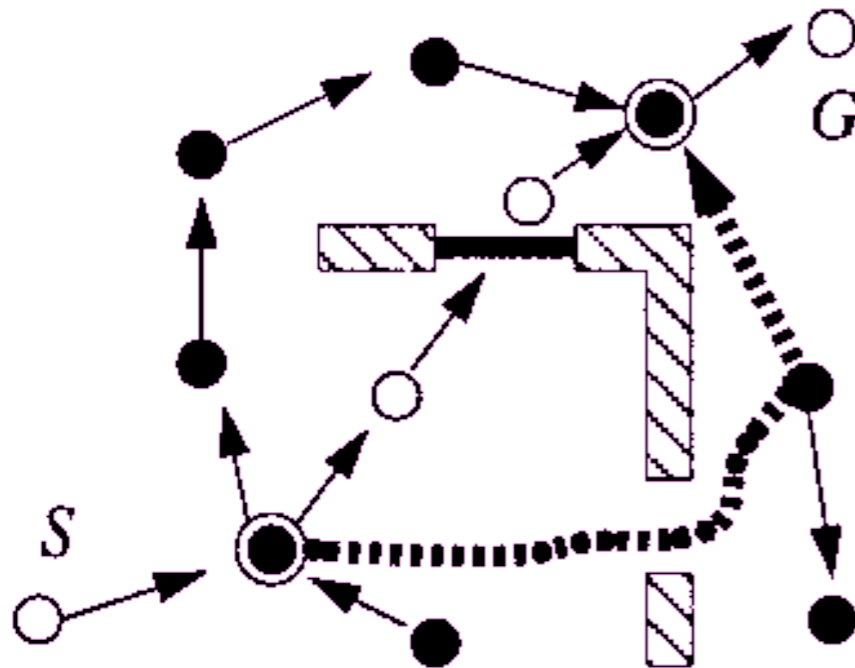
The map shows the computed home vectors for all positions in our toy house arena. The catchment area is depicted in blue, trajectories of the homing robot in red.



The above image shows the image distance map for a snapshot taken in the center of a toy house arena. The color temperature corresponds to the minimum distance which can be obtained by rotating the respective views



Cognitive Mapping: Motivation



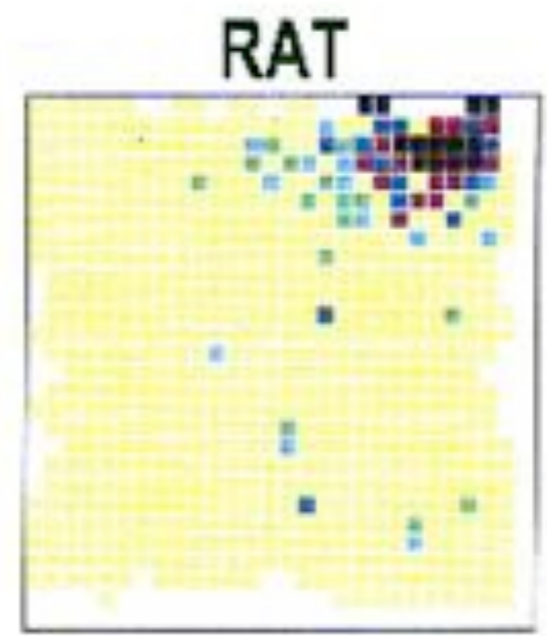
Franz et al. (1998): algorithmic graph model

Arleo et al. (2001): non-topological place cell model

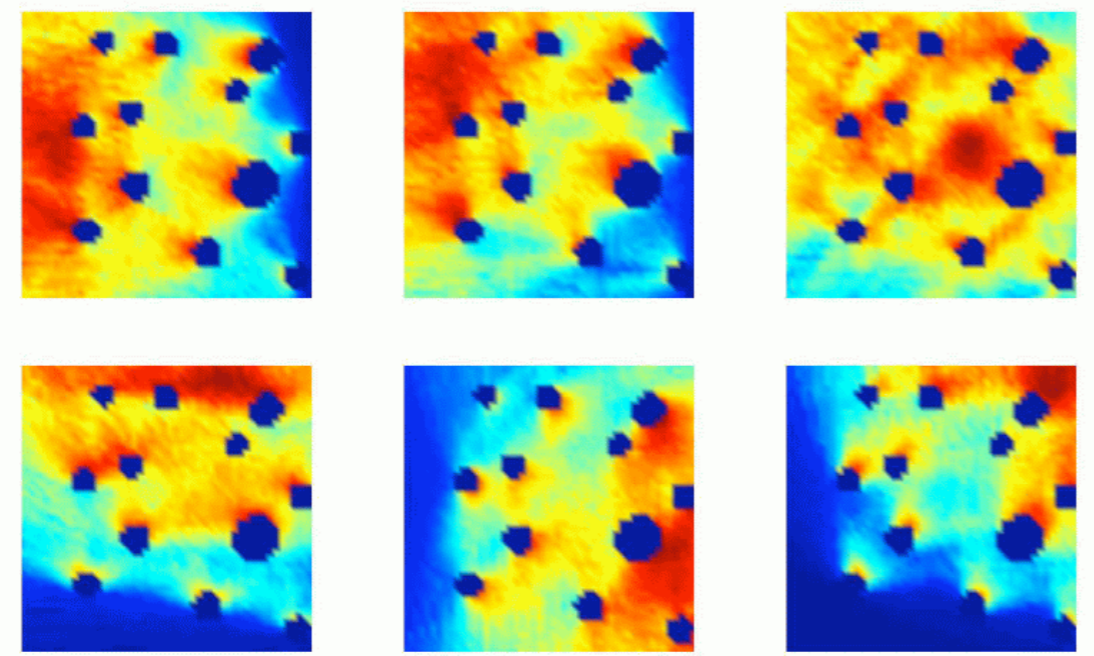


Neurophysiologie

Place cells im Hippocampus (Gehirnregion) der Ratte



Ratten place field

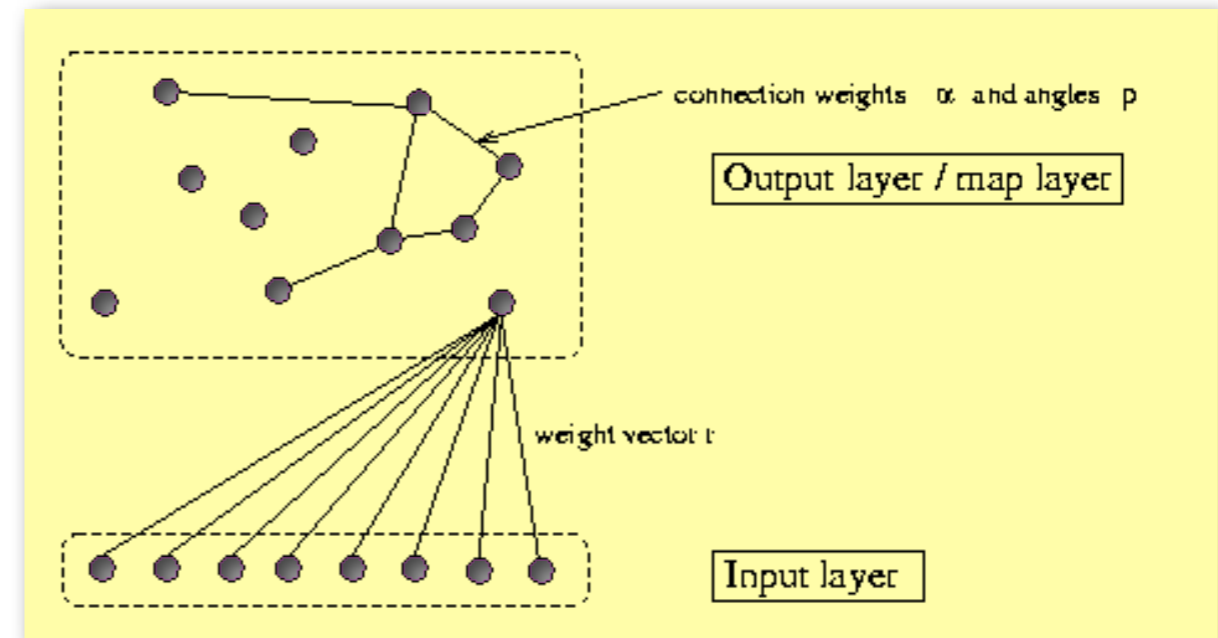


Roboter place fields



Place Cell Modell

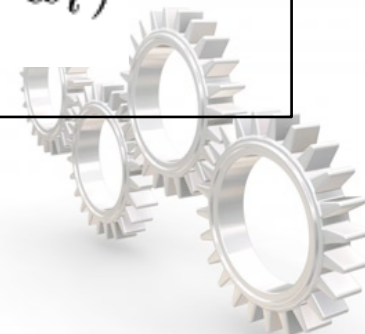
Hafner (2000), Learning Places in Newly Explored Environments,
In: Meyer, Berthoz, Floreano, Roitblat and Wilson (Eds.), SAB2000 Proceedings Supplement Book, pp. 111-120



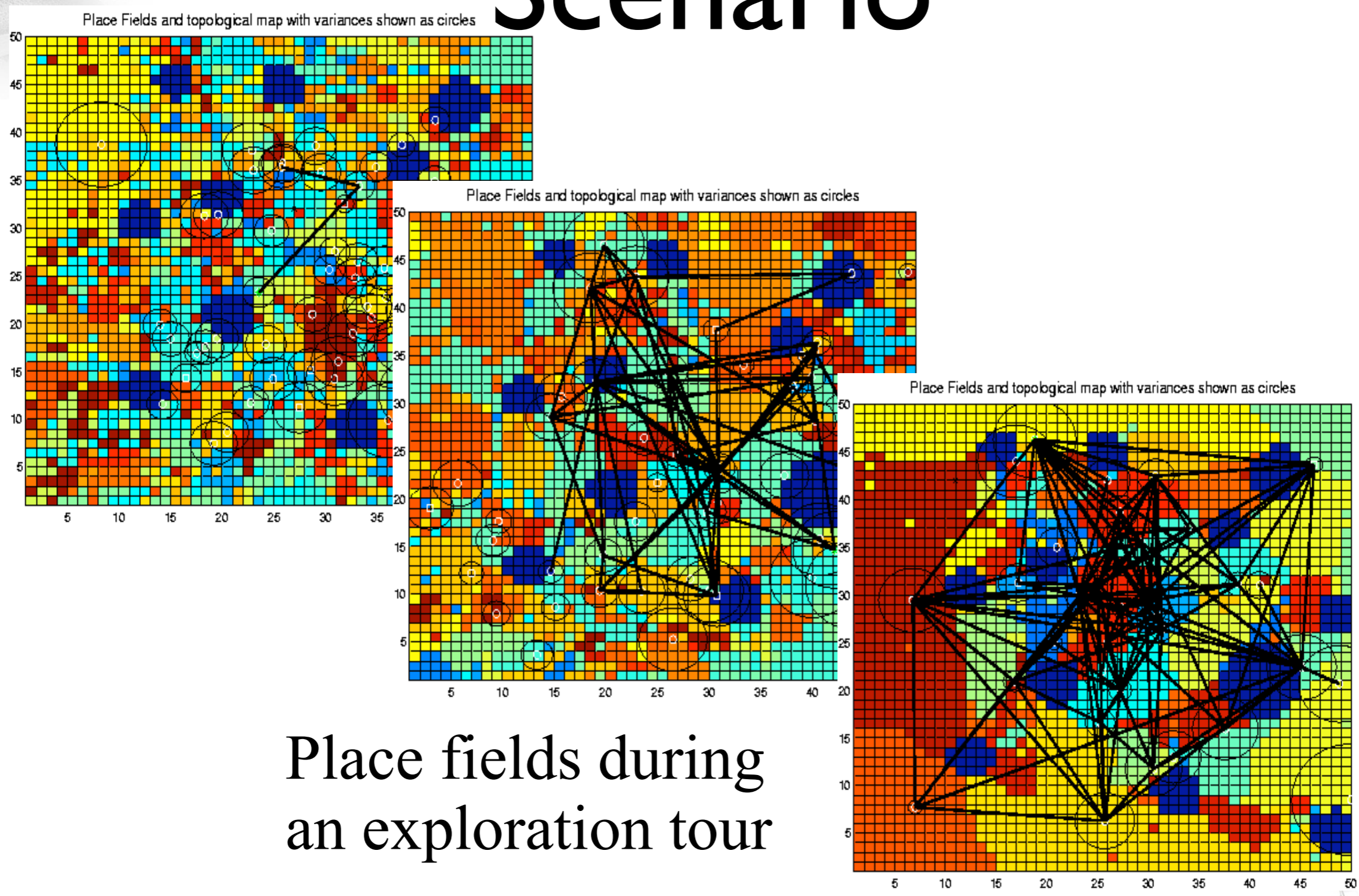
SOM Learning:

Receptive fields $\Delta w = \eta_1 (v - w)$

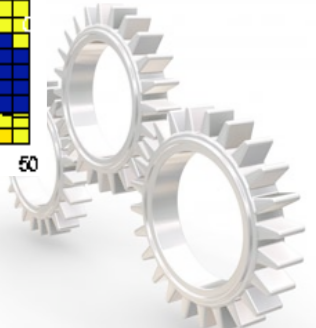
Lateral weights $\Delta w_l = \eta_2 a_1 a_2 (1 - w_l)$



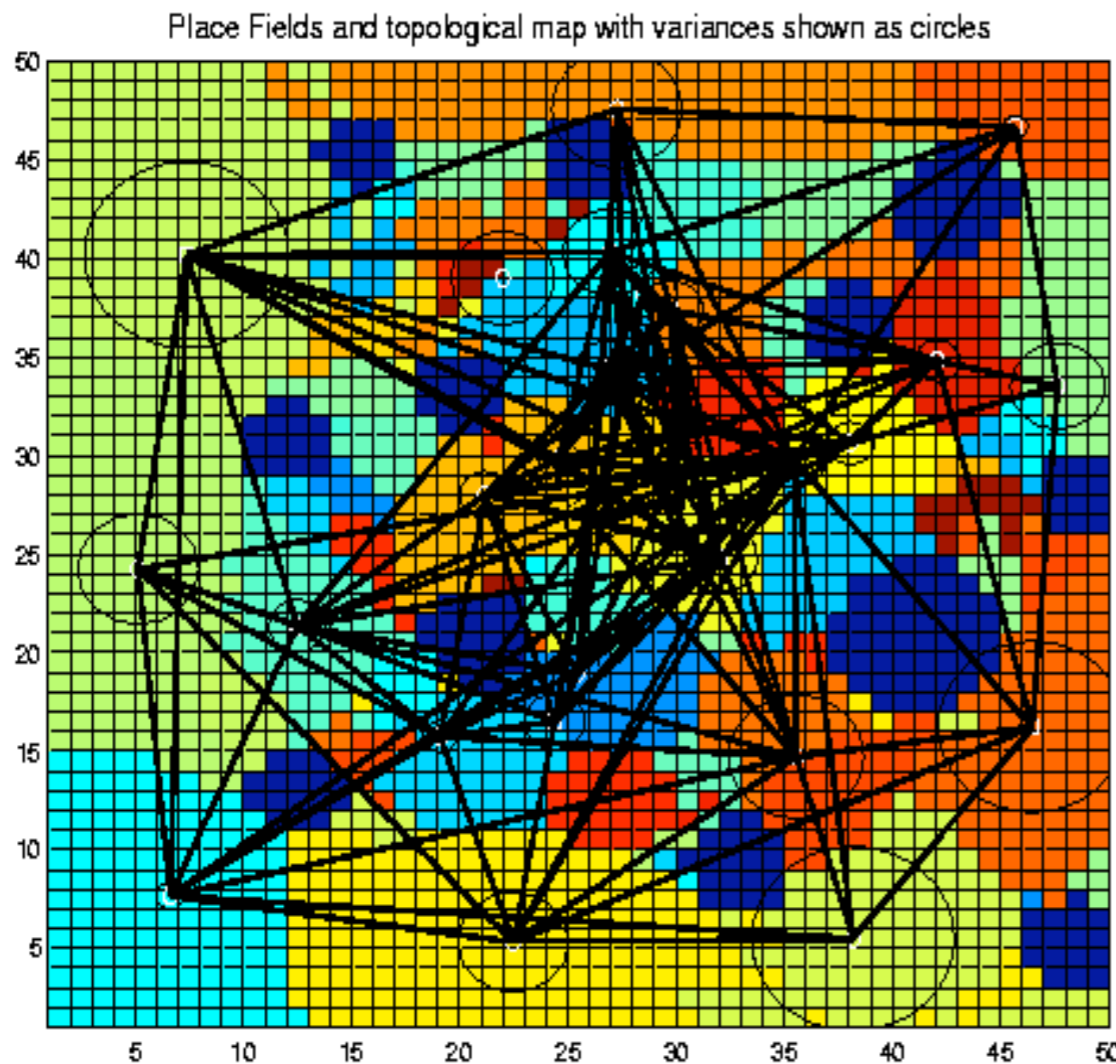
Cognitive Map Learning Scenario



Place fields during an exploration tour



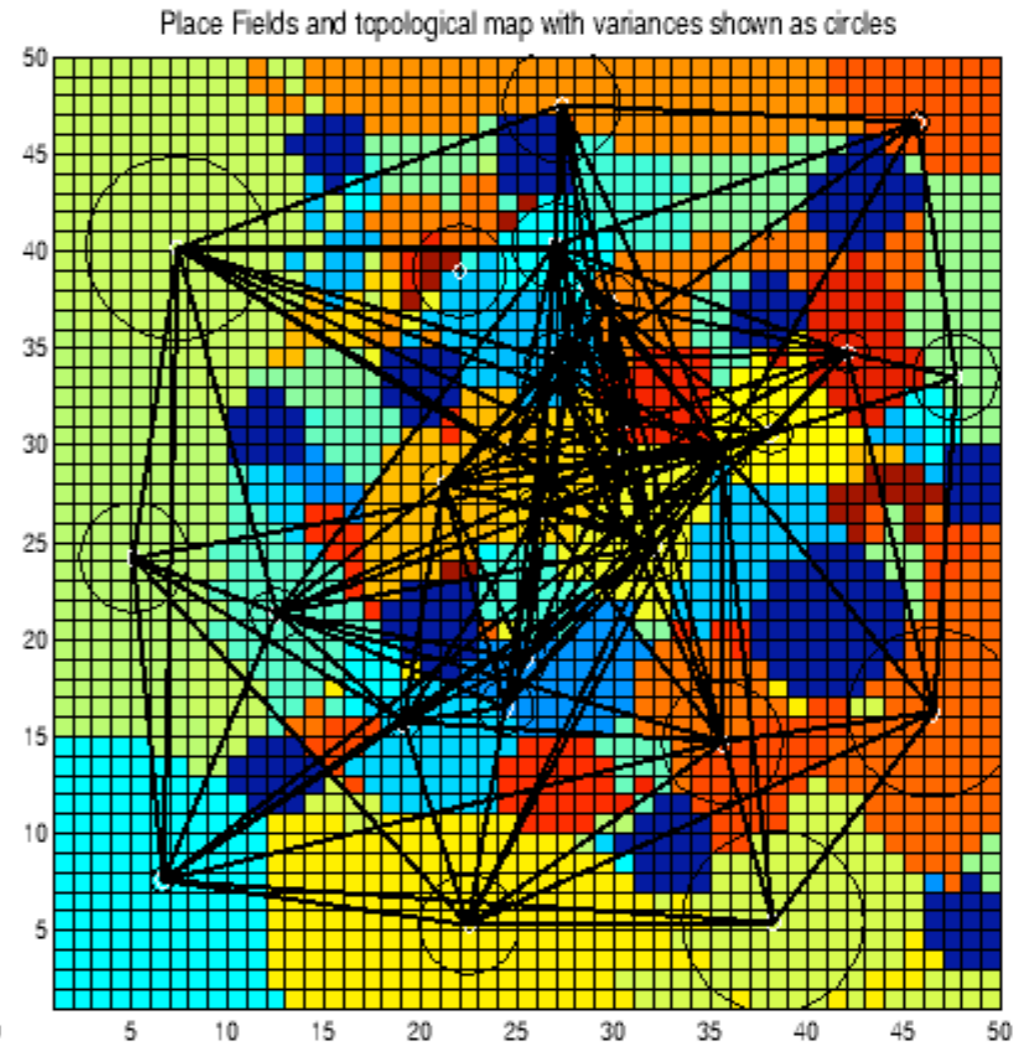
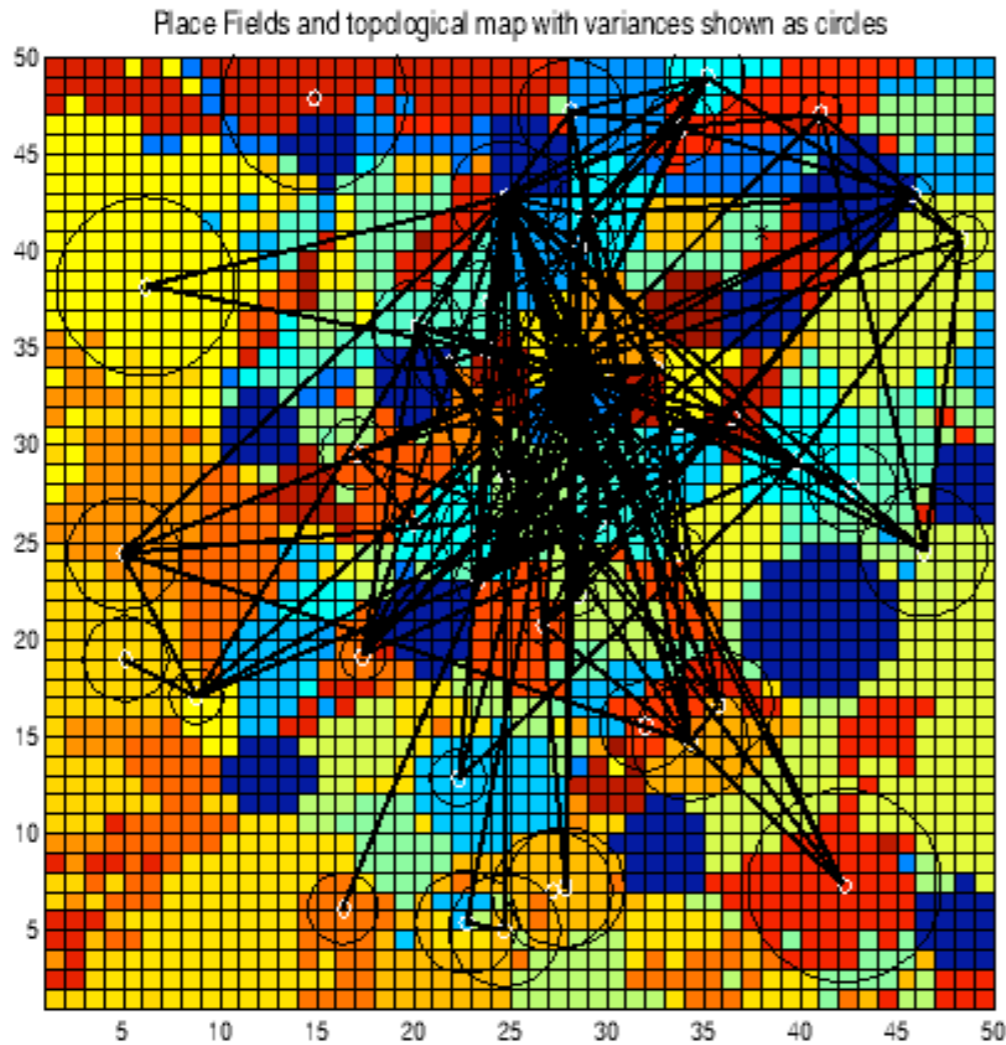
Place Field Densities



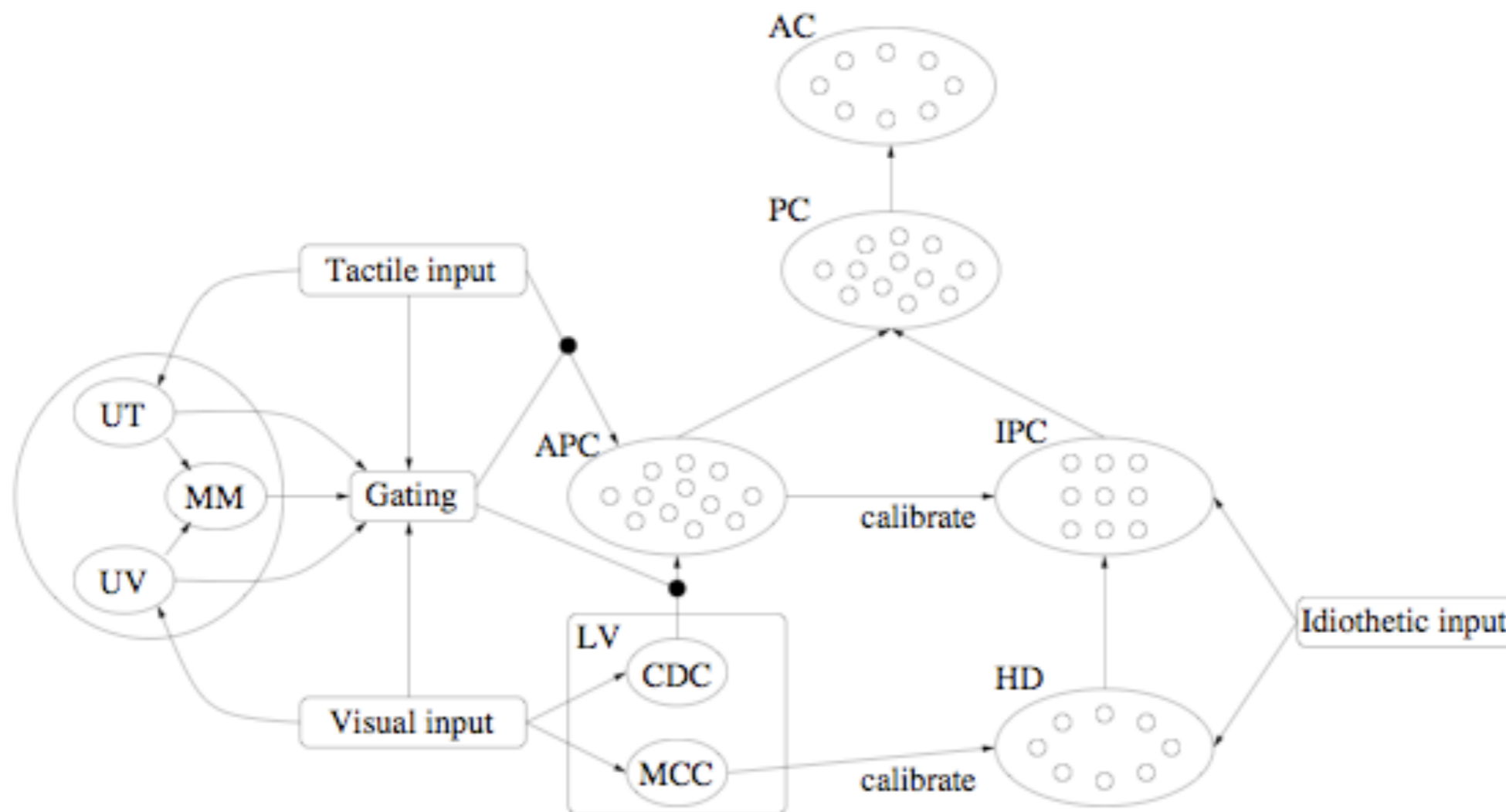
- Die Dichte der Place Fields ist in der Nähe von Hindernissen größer als am Rand
- Gleiche Messungen bei Ratten
- Interpretation: „interessante Orte“



Evolving Optimal Learning Parameters



Place cell modell



Strösslin, 2004



Place cell modell

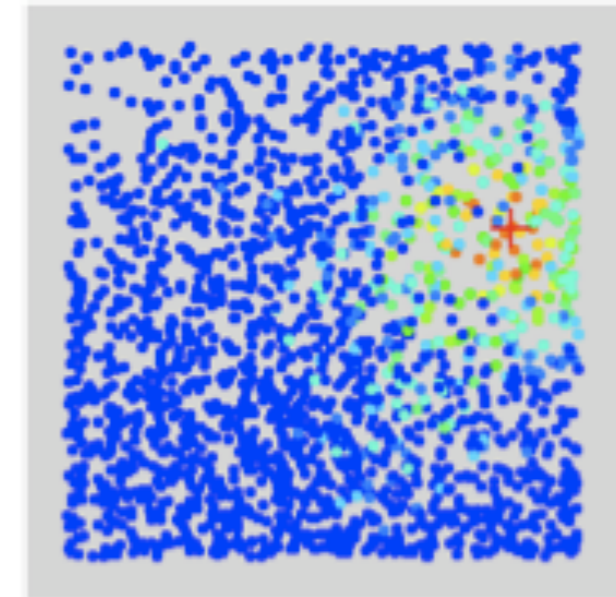
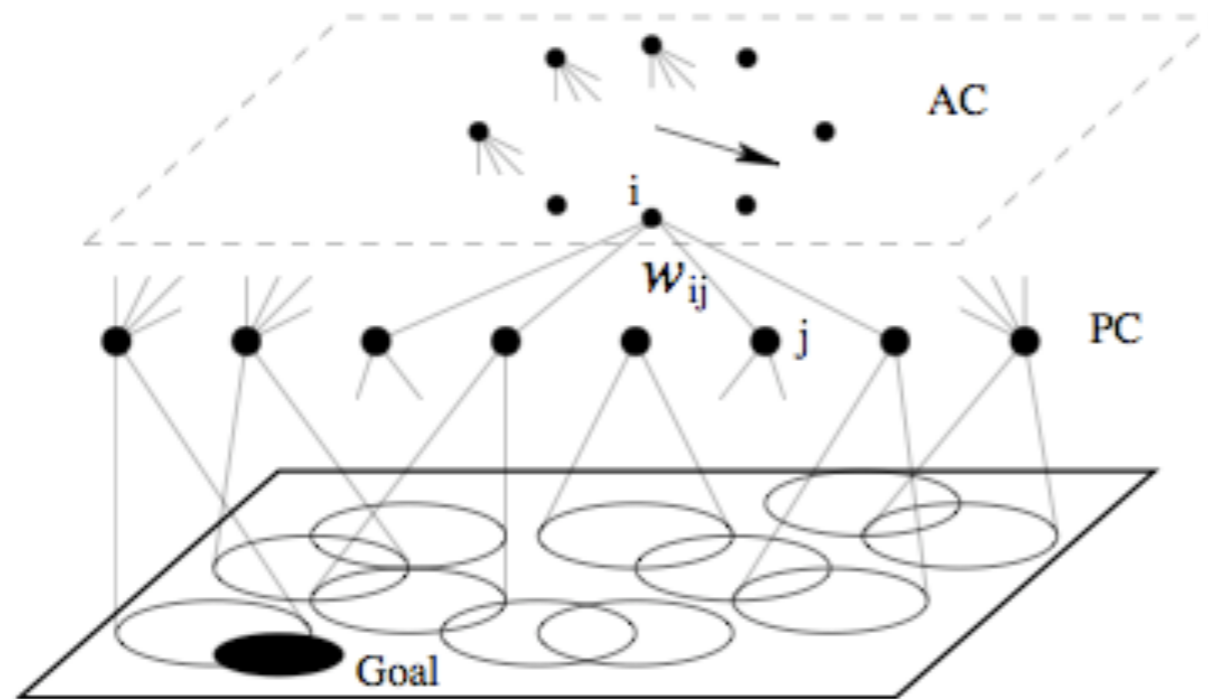


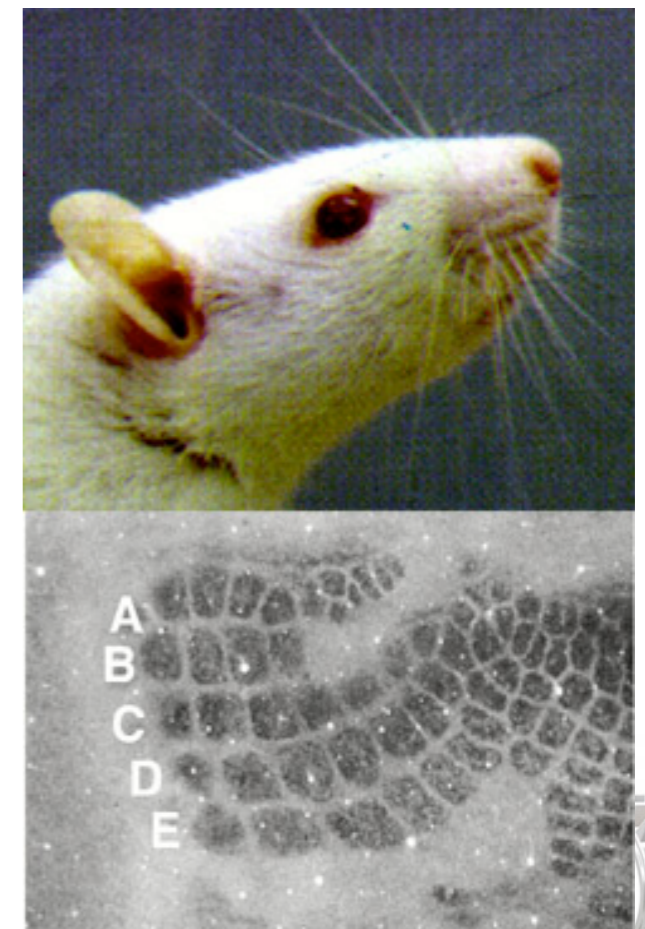
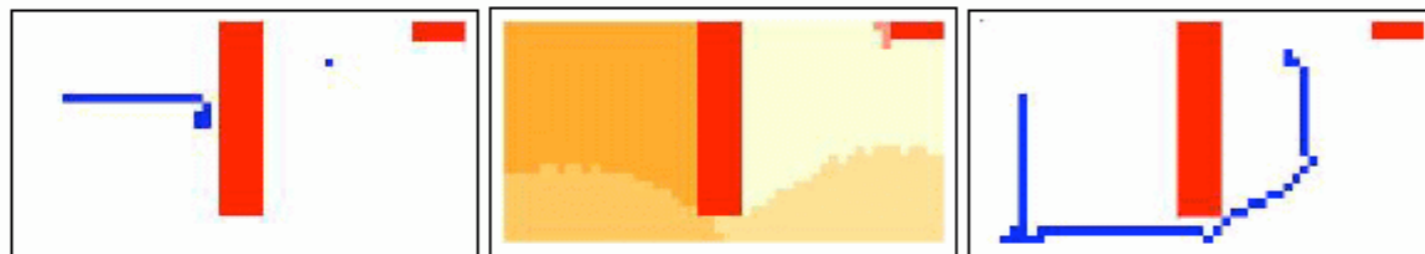
Figure 8.1: Architecture of our navigation system: A layer of hippocampal place cells (PCs) represent the environment. Each PC is active in a region of the environment and their receptive fields overlap. In order to learn to navigate to the goal, PCs are connected to action cells (ACs) which code for the direction of the next movement. The population vectors of both layers allow a continuous interpretation of position (PCs) and direction of movement (ACs).

Strösslin, 2004



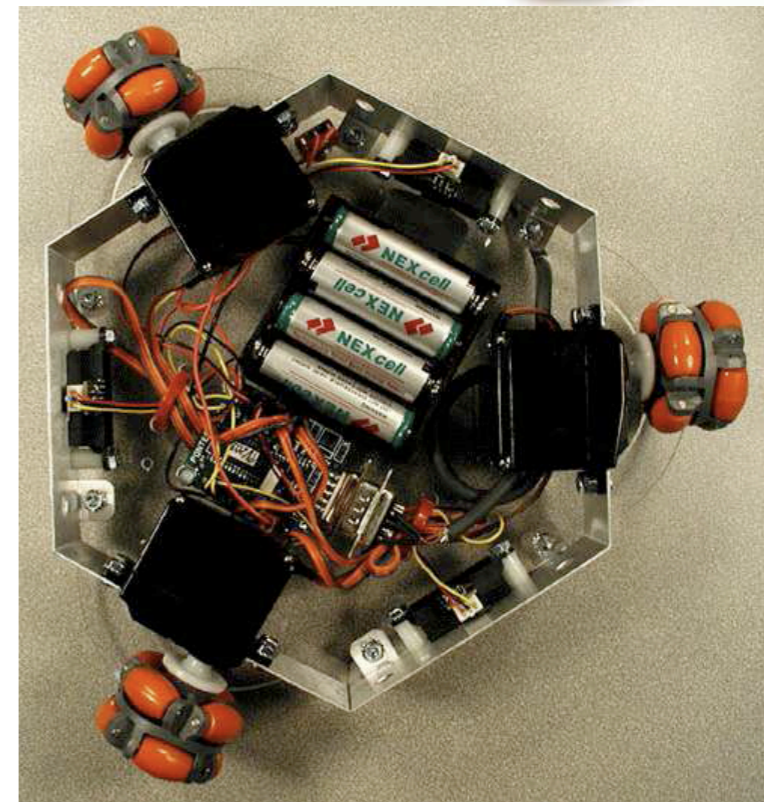
Combining Navigation Strategies

Visuelles Homing als Baustein für kognitive Karten

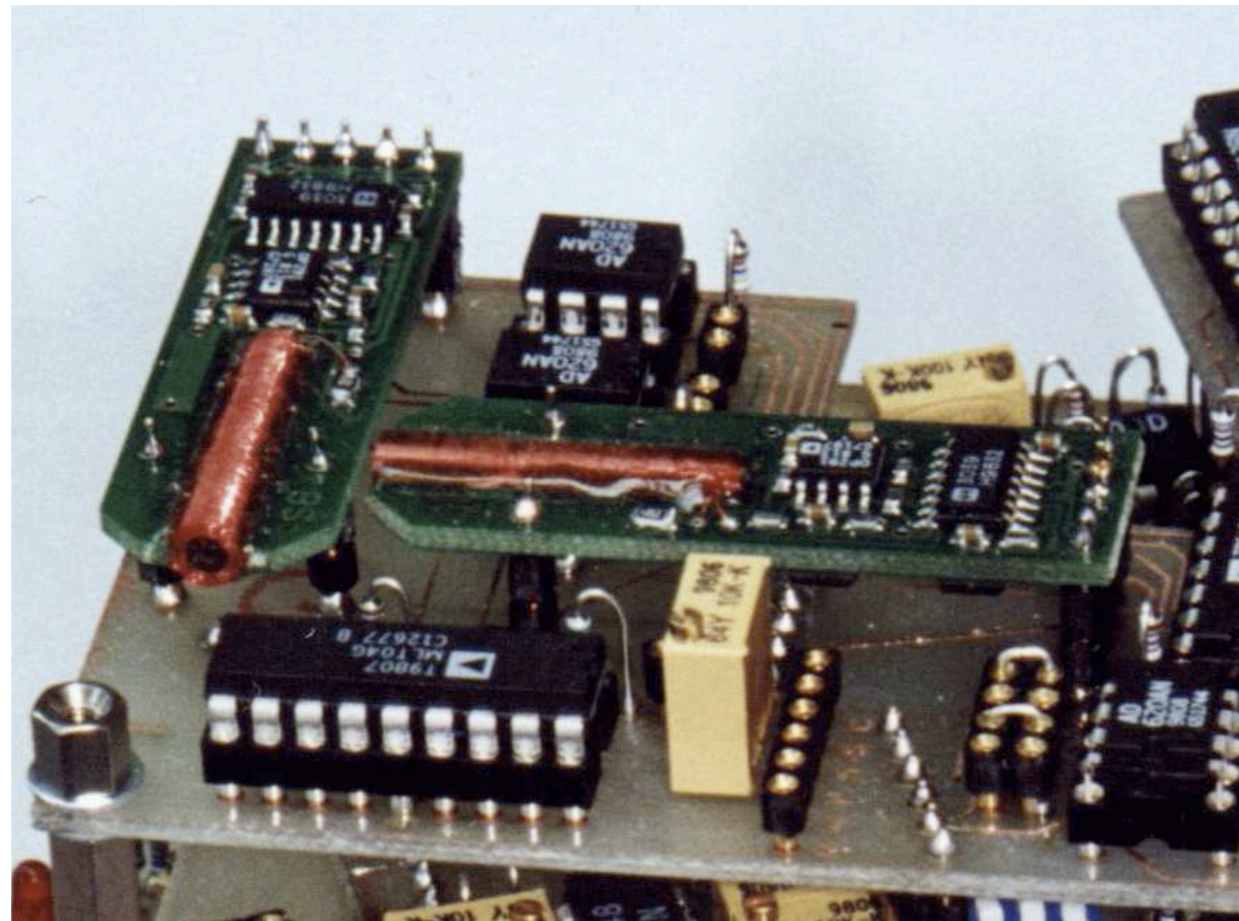


Steuerung

- Holonomes Rad mit passiven Rollen
- Palm Pilot Robot Kit
Carnegie Mellon University
Robotics Institute



Fluxgate Kompass



Geometrische Karten

- allgemeinste Form der Navigation ("Übersichts~"):
- Navigation zu noch nie besuchten Orten möglich
- Navigation auf noch nie gefahrenen Wegen möglich (spatial reasoning, z.B. Finden von "Abkürzungen")
- Repräsentation für Menschen verständlich
- Karten-Erstellung bzw. Karten-Aufbau aufwendig
- Aufbau: Unsicherheit bei Positionsbestimmung ("Henne-Ei-Problem")
- aufwendige Datenstrukturen (?)



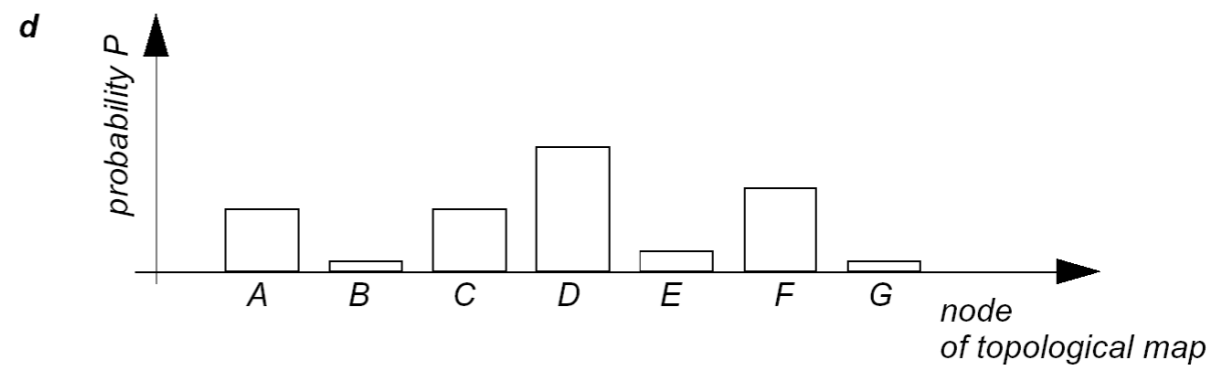
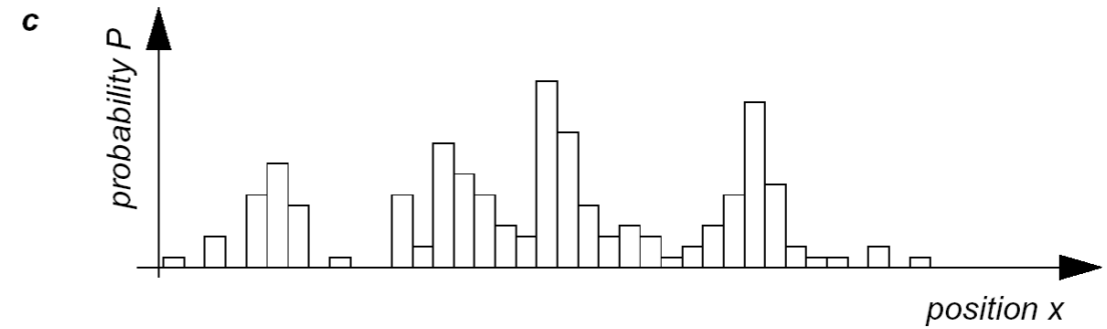
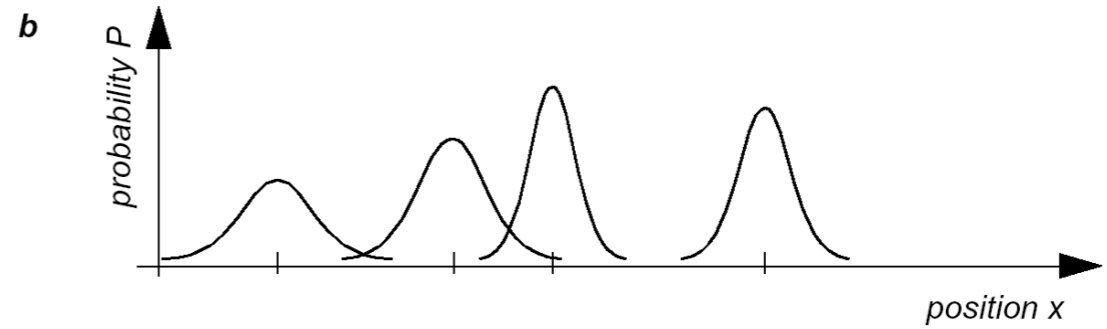
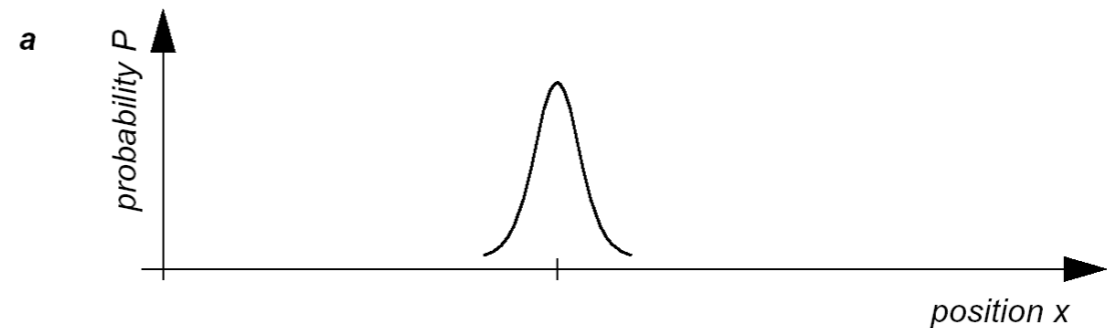
Probabilistische Lokalisation

- Odometriefehler (Rutschen, Raddurchmesser...)
- Fehlermodell der Odometrie des Lokalisationsproblems
- probabilistische Formulierung (verschiedene Repräsentationen)
- "Belief" über Position (\sim Wahrscheinlichkeit)
- Aktualisierung des Beliefs unter Berücksichtigung von Aktions- und Sensormodell
- Sensormodell
- sensorische Messfehler (Rauschen)

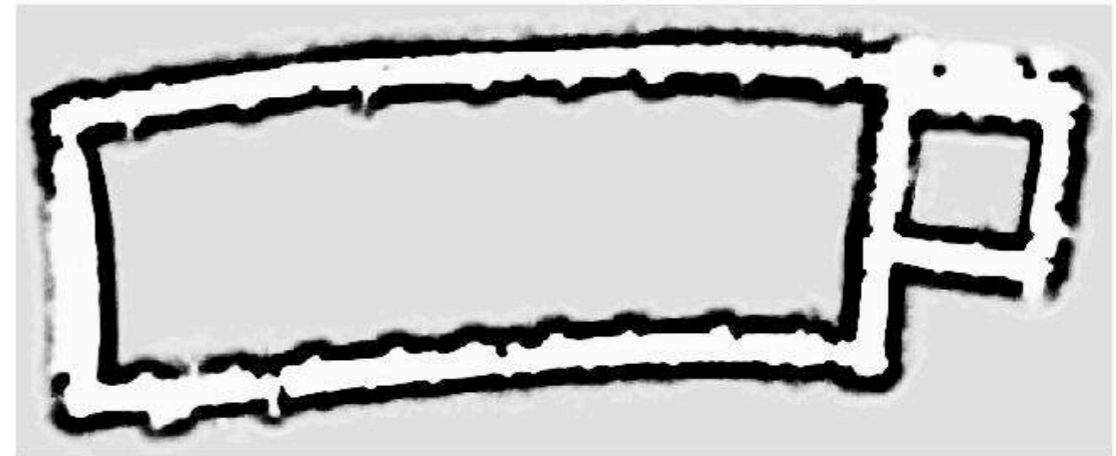
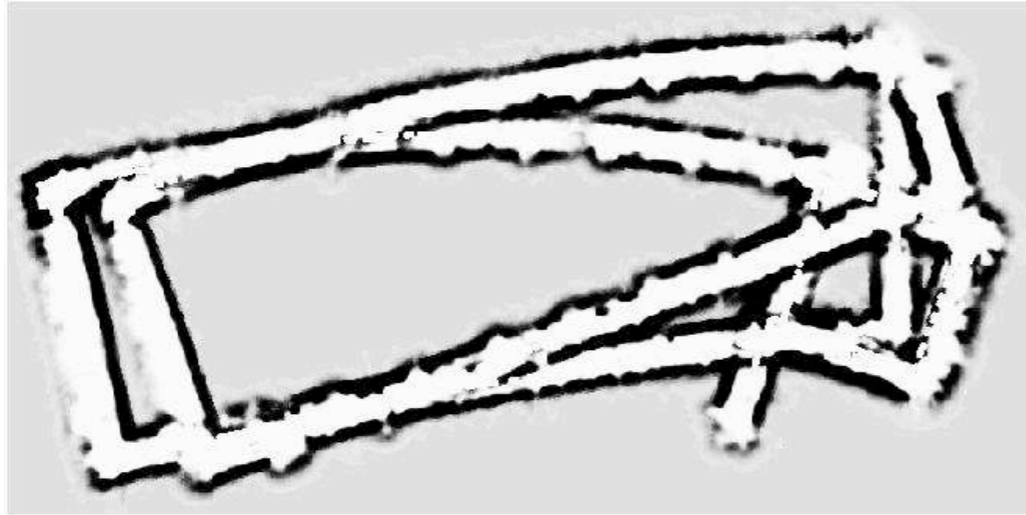


Belief Representation

- a) Continuous map with *single hypothesis*
- b) Continuous map with *multiple hypothesis*
- c) Discretized map with probability distribution
- d) Discretized topological map with probability distribution



SLAM



- zentrales Problem bei SLAM: "loop closure" in zyklischen Umgebungen
- lange Fahrt durch unbekanntes Terrain, Karte wird aufgebaut,
- Odometriefehler führen zu Verzerrungen
- Roboter trifft wieder an zuvor besuchtem Ort ein,
- Karte muss so korrigiert werden, dass der Zyklus geschlossen wird





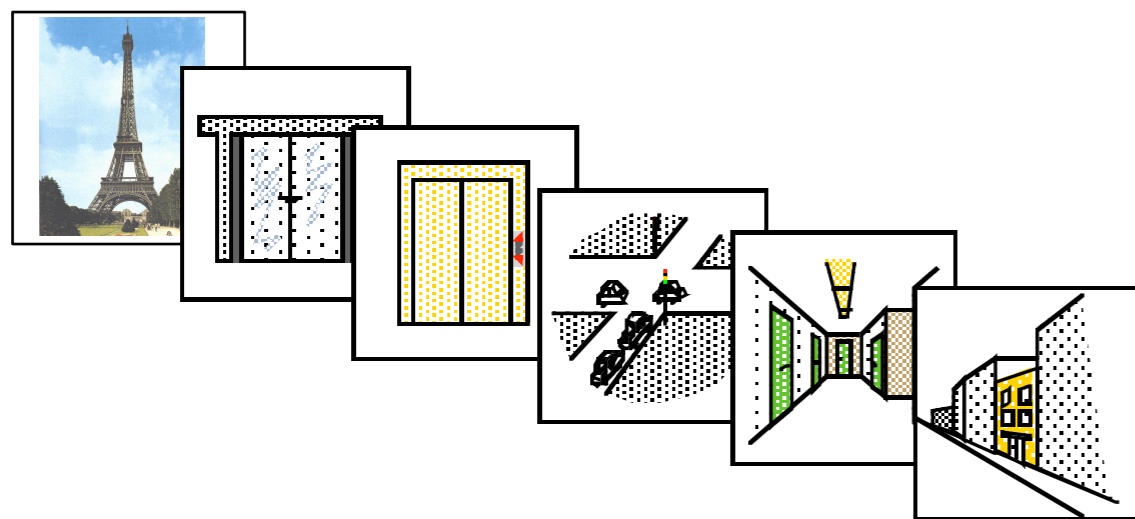
Korrelation von Scans

- Translation
- Rotation
- Kreuzkorrelation der Winkel Histogramme

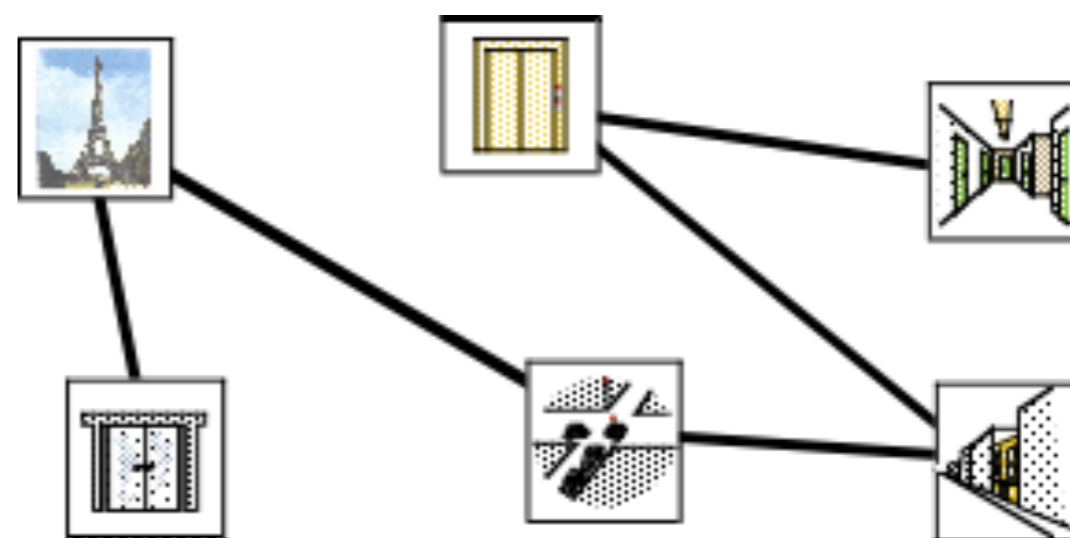


Environment Representation: The Map Categories

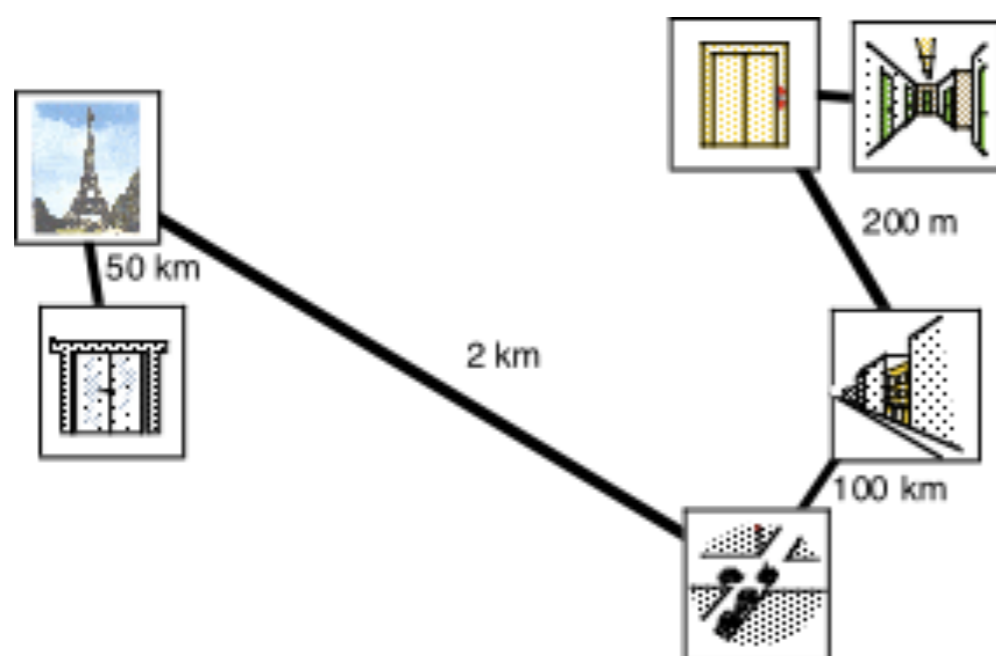
1 Recognizable Locations



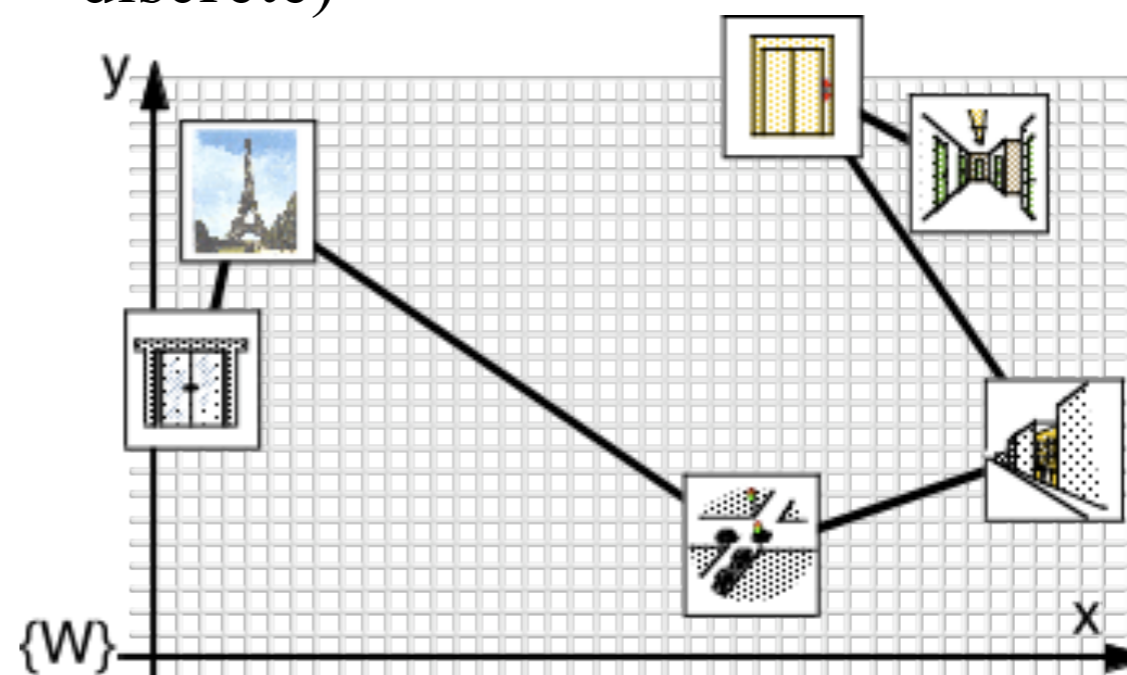
1 Topological Maps



1 Metric Topological Maps

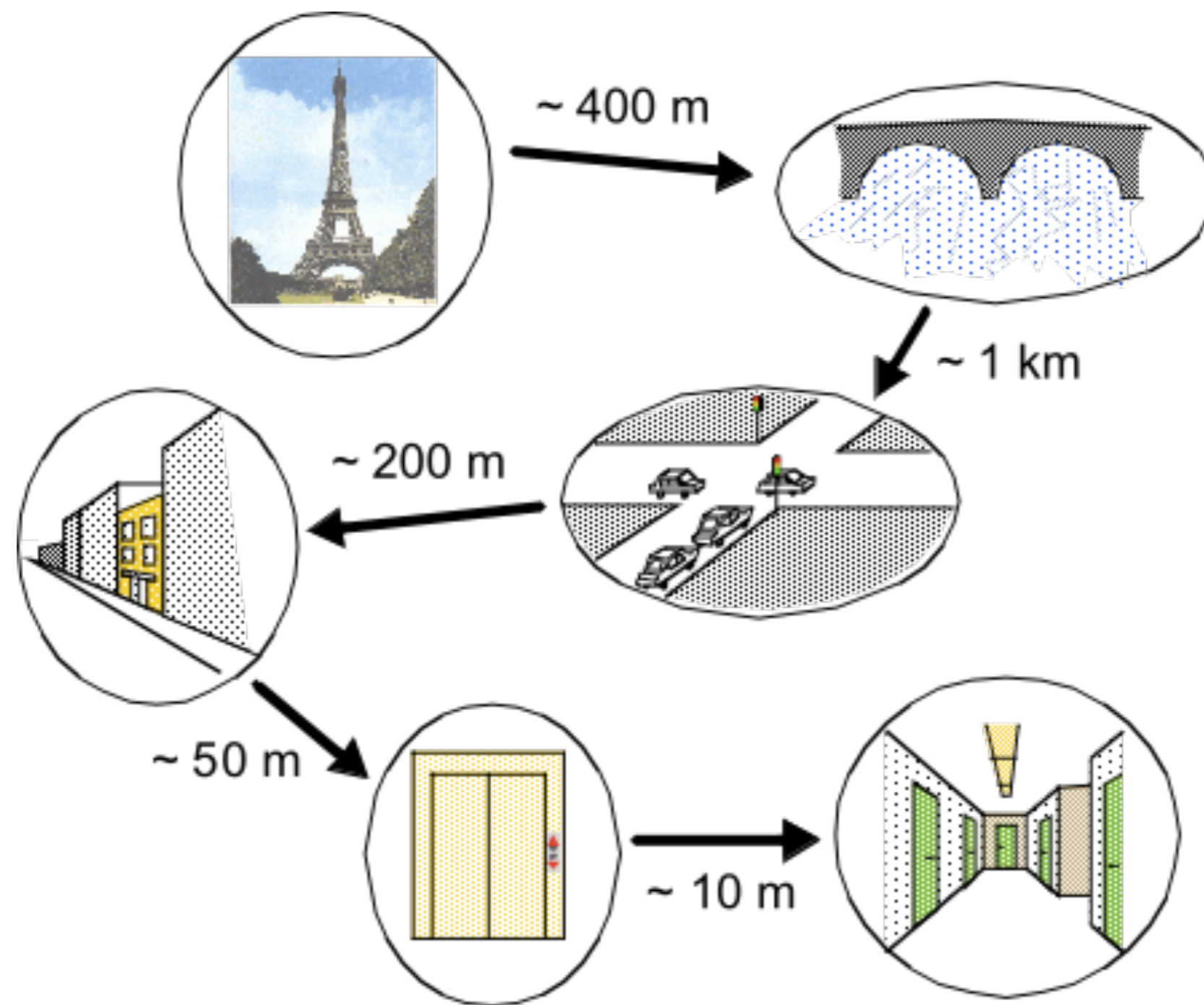


1 Fully Metric Maps (continuous or discrete)



Courtesy K. Arras

Human Navigation: Topological with imprecise metric information



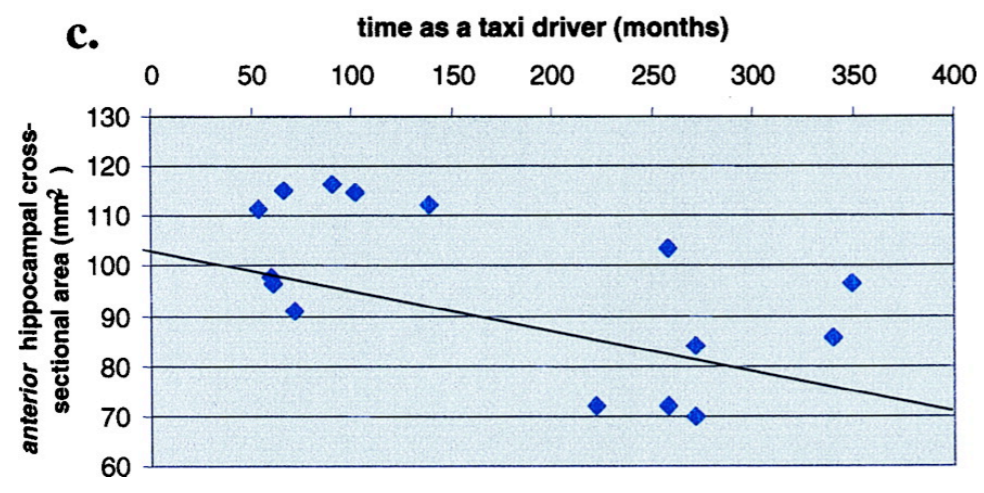
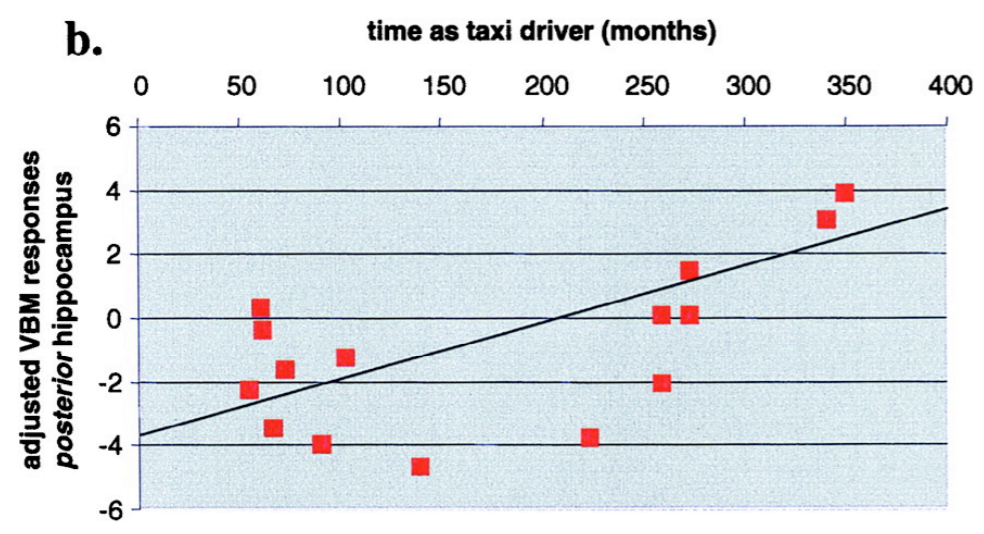
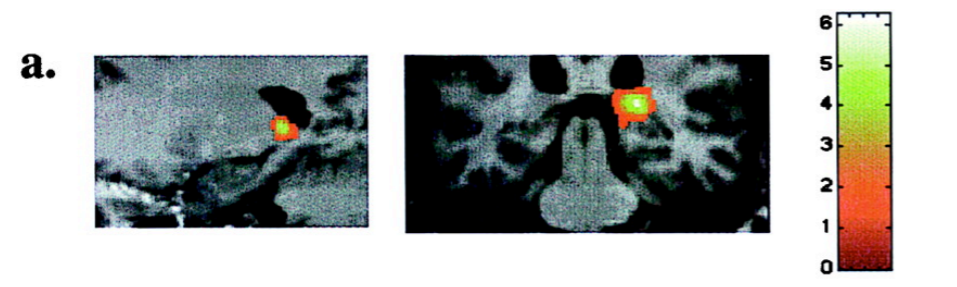
Courtesy K. Arras

Navigation - menschliches Gehirn

- Studie bei Taxifahrern in London
- In order to drive a traditional black cab in London drivers have to gain "the knowledge" - an intimate acquaintance with the myriad of streets in a six-mile radius of Charing Cross.
- größerer Hippocampus



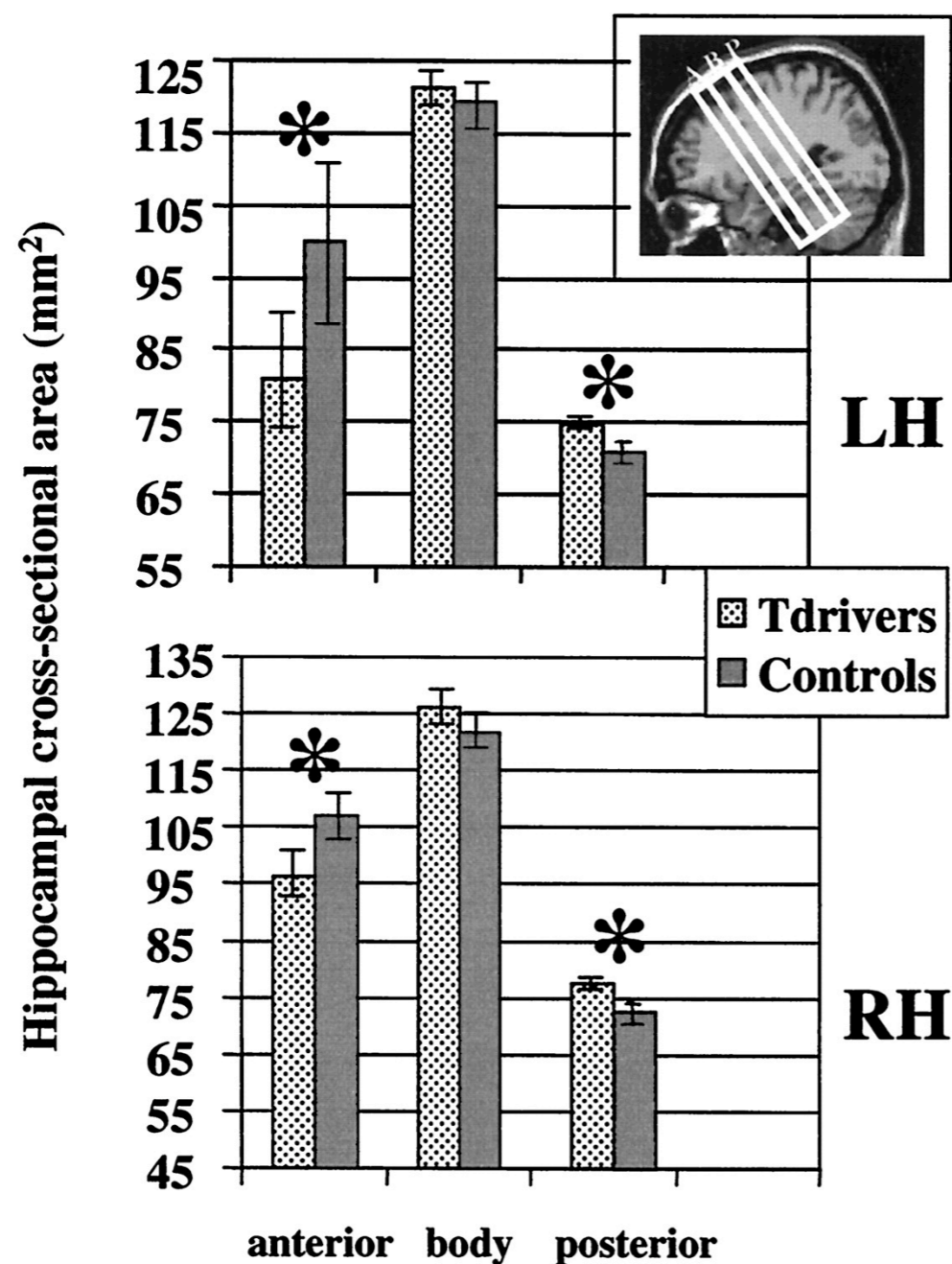
Navigation - menschliches Gehirn



- Maguire et al. (2000), *Navigation-related structural change in the hippocampi of taxi drivers*



Navigation - menschliches Gehirn



- Maguire et al. (2000), *Navigation-related structural change in the hippocampi of taxi drivers*



Human Navigation

Virtual Tübingen, MPI for Biological Cybernetics



Human Navigation

Virtual Tübingen, MPI for Biological Cybernetics

Pano Lab



VR Lab



Das Labor besteht aus einer großen gekrümmten Projektions-Leinwand (einem Halbzylinder von 7 Metern Durchmesser und einer Höhe von 3,15 Metern). Ein Grafikcomputer aus der Onyx2-Serie verarbeitet sehr detaillierte Bilder, die auf die gekrümmte Leinwand projiziert werden. Geeignete Hardware für einen sanften Kanten-Übergang wird benutzt, um drei Einzelbilder, die von drei CRT-Projektoren erzeugt werden, zu einem einzigen Bild zu verschmelzen. Dieses Bild besteht aus 3500 x 1000 Pixeln. Für einen Beobachter, der im Zentrum des Zylinders sitzt, überdeckt es einen Blickwinkel von 180 Grad in horizontaler und 55 Grad in vertikaler Richtung.

Verena V. Hafner, Kognitive Robotik 2008/2009, HU Berlin






Human Navigation

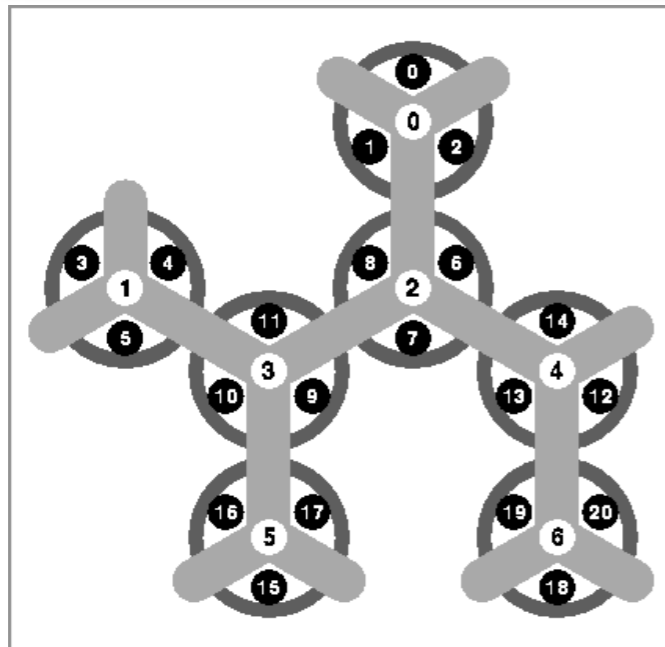


Virtual Tübingen
<http://virtual.tuebingen.mpg.de>

Max Planck Institute for
Biological Cybernetics 



Hexatown



Mallot, H.A. and S. Gillner: Route navigation without place recognition: what is recognized in recognition-triggered response? (2000)



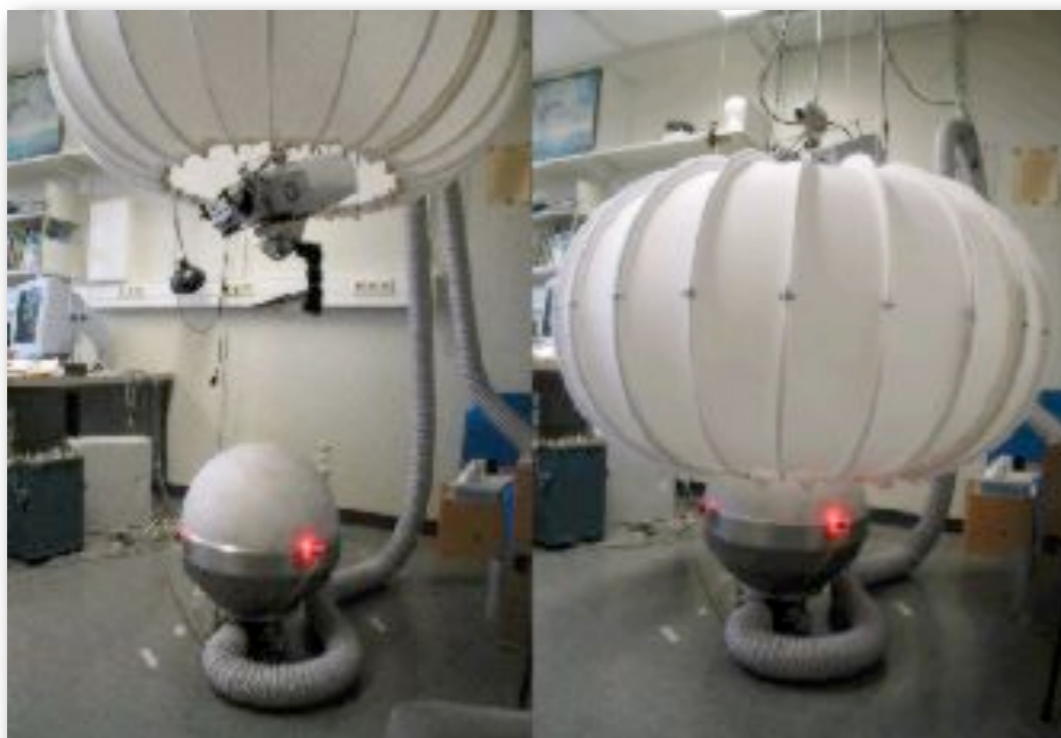
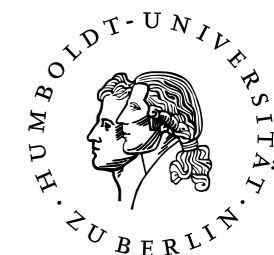
Hexatown

- Navigations-Aufgabe:
- Einfluss von Landmarken (global-lokal)
- Place-recognition vs. view-recognition
- geometrische Struktur
- 3D Informationen (Hügel)
- Unterschiede Frauen/Männer





Virtual Reality for Rats



- Vergleich
möglich
zwischen
- Menschen
 - Ratten und
 - Robotern!



Universität Tübingen

