Technological Educational Institute of Crete

Mobile Robot Position Estimation using unsupervised Neural Networks

George Palamas, George Papadourakis and **Manolis Kavoussanos**

Introduction

Localization is a term for the task of identifying places in the environment after prior exploration and map-building by the robot

Localization is one of the foundamental problems to be solved when designing a navigation system. If a robot does not know where it is, it cannot efectivelly plan movements or reach target positions

Cases to be considered

- continuous localization (position-tracking or relative positioning)
  - **an initial estimate of the robot's position is available**
  - **Comon method to keep track of the position relies on odometry**
  - **need for a mechanism that can update the correct location of the robot.**
  - **errors in the estimate are accumulated (wheel slippage, uneven floors, etc).**

- lost robot problem (global localization or absolute localization)
  - **no initial or approximate estimate is available**
  - **explicit model of environment needed**

- **SLAM (Simultaneous Localization and Mapping):How does a mobile robot simultaneously localize and build maps of the environment in an unknown environment**

General Methods to mobile Robot Global Self-Localization

- Using active beacons, the transmitter of these usually uses light or radio frequencies.
  A popular implementation is the Global Position System (GPS)
  Promising to become universal navigation solution for almost all Automated Vehicle systems
  However, this system cannot be used indoors
- Landmark based method, distinct features in the environment can be detected and intentified by the robot (e.g. doors, corners, patterns on the floor)
- Probabilistic techniques, current robot's perception is matched against a world model of the environment
  - Markov Localization
  - Monte Carlo Localization
- Dead Reckoning
  - Kalman filters

Bio-mimetic Robot Navigation

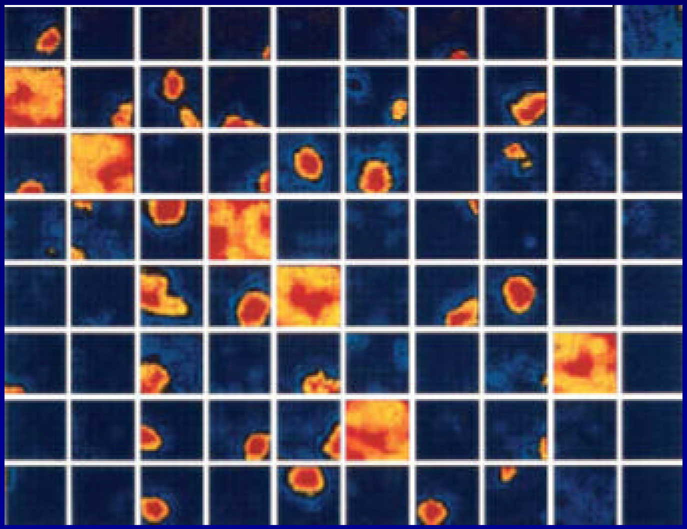
Biologically Inspired Robots: Capturing behaviors of biological systems such as ant colonies, snake movements onto robots to perform tasks that otherwise prove difficult

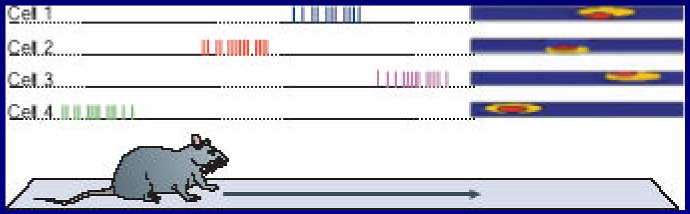
- **Animal navigation principals**
  - **Animals learn to navigate using data gathered from interacting with the world**
  - **High degree of system autonomy in unstructured environments (even for insects like bees or ants)**

- **Prerequisites for realistic service robotics**
  - **No need for special apparatus such as radio beacons or Global Position Systems (GPS)**
  - **Avoid modifications to surrounding environment (e.g. artificial landmarks)**
  - **No need for a-priori knowledge of the environment at the design time**
  - **Ability to perform in dynamically changing environments**
  - **Adaptability in a way that excludes human operators**

Place Cells

- Place Cells in rodent brains (O'Keefe &Dostrovsky, 1971): neurons found in part of the brain called hippocampus
  - Neuron activity correlated with the rat's position in an environment
  - Activity depends largely on visual cues
  - Sensitive to animals motion (still active in the dark)



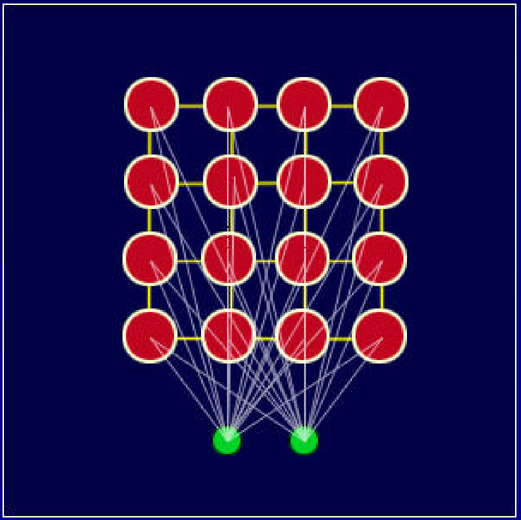


Hippocampal neurons firing patterns [Kazu Nakazawa et.al, 2004]

Human Hippocampi with extensive navigation experience (taxi drivers) were significantly larger than those of control subjects *(Frackowiak, 2000)*

Kohonen's Self Organizing Feature Maps

- SOMs learn to classify data *without supervision*
- Representation of multidimensional data in much lower dimensional spaces usually one or two dimensions
- Information storage in a way that any topological relationships within the training set are maintained.



Training data consists of vectors, *V*, of *n* dimensions:

V1, V2, V3...Vn

Each node contain a corresponding weight vector *W*, of *n* dimensions:

W1, W2, W3...Wn

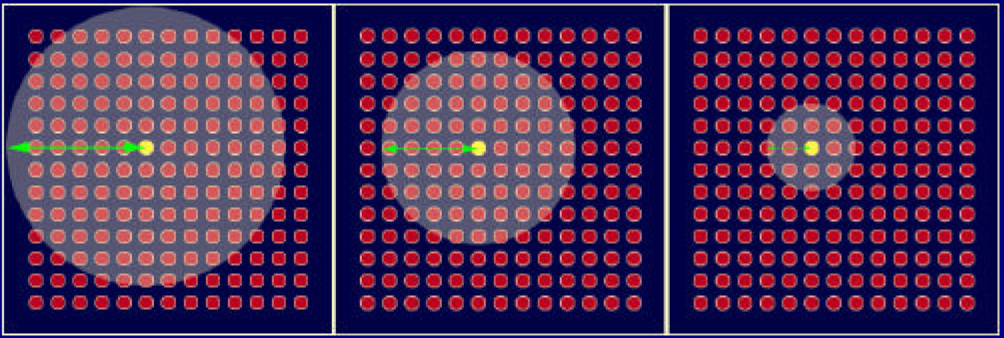
Learning Algorithm Overview

- **Weights initialization (typically to small random values)**
- **Calculate the Best Matching Unit**

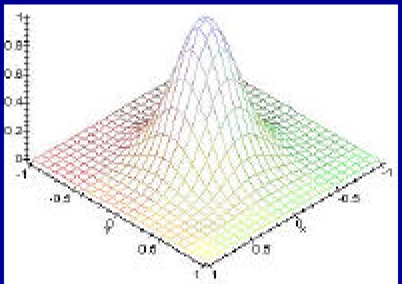
$$Dist = \sqrt{\sum_{i=0}^{i=n} (V_i - W_i)^2}$$

V is the current input vector and ***W*** is the node's weight vector

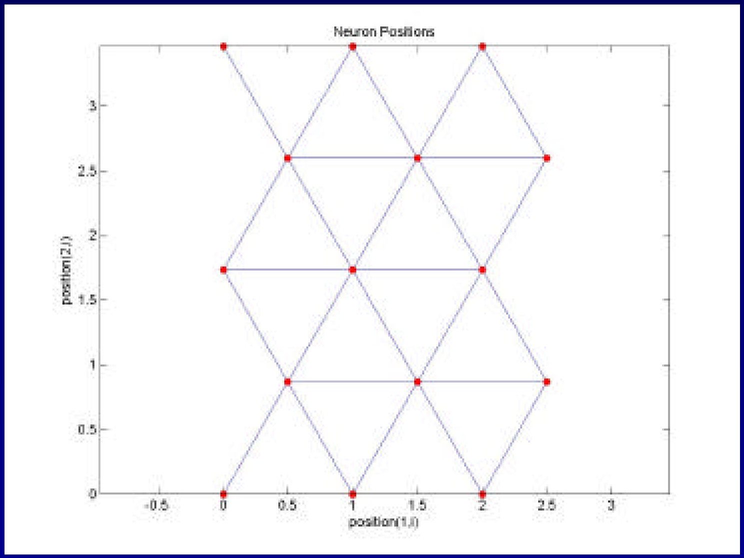
- **Determining the Best Matching Unit's Local Neighbourhood**



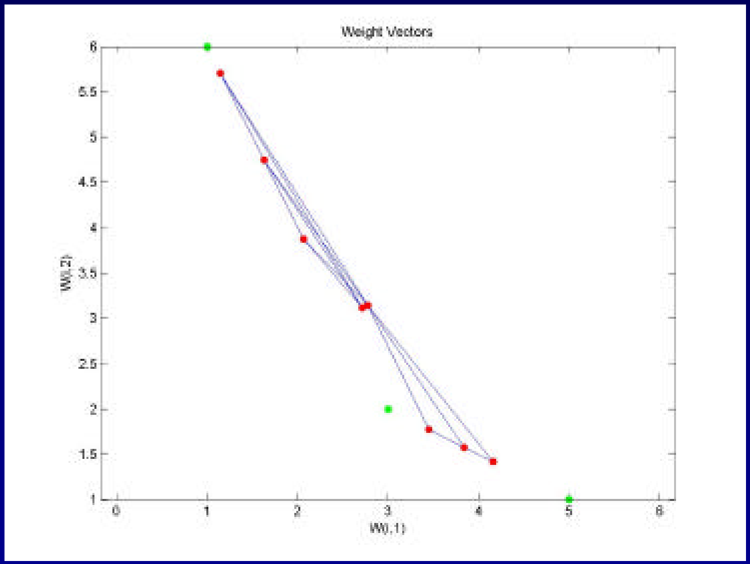
- **Adjusting neighbor Weights (e.g. Gaussian function)**



Topology Preserving



Initial position of nodes



Position after training

Unsupervised Learning for Robot Navigation

Task

Autonomous robot navigation in an unknown environment

Goals

- Find a useful internal representation
- Let the robot build/learn the map itself

Challenges

- navigate independently of changes in the scene (Light conditions, reallotment of furniture before or after learning cycle, animals or pets walking around)
- Efficiency on handling noisy sensor information.
- Elimination of perceptual aliasing
- Low computational cost for a time-realistic position estimation mechanism

Approach

Self organization of perceptual signatures (sensor input vectors)

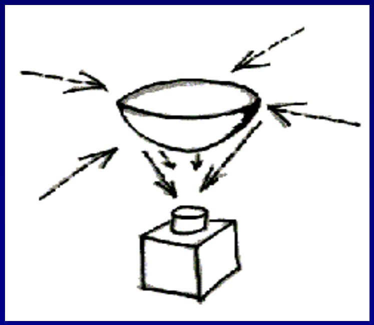
Sensors and Honeybees

❑ Infrared and Ultrasonic sensors

- ➢**Short range, may imply interference and wraparound**
- ➢**Both are cheap and easy to use**
- ➢**Usually no need for preprocessing is required**

❑Vision sensors

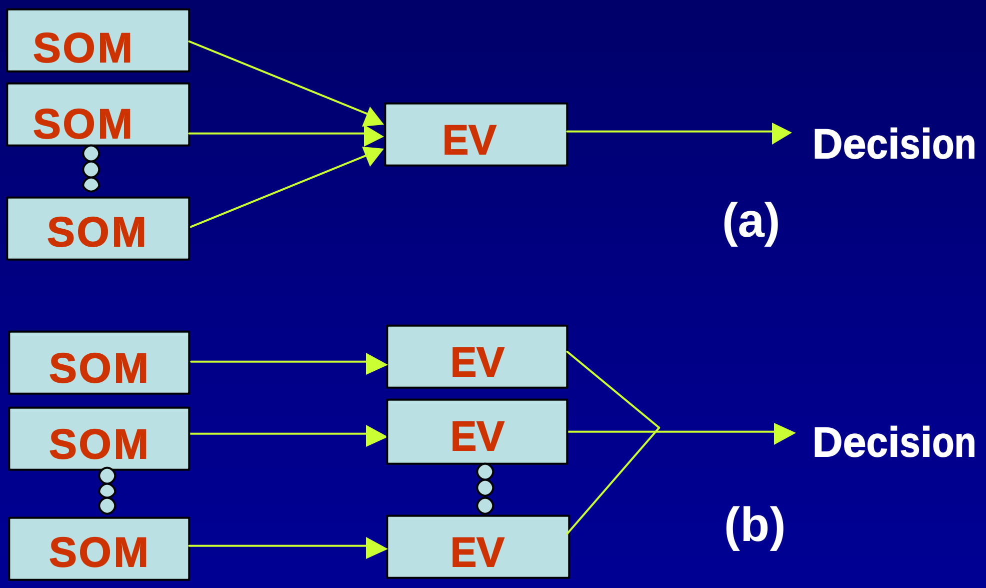
Provide the richest source of information
Dificult to obtain meaningful information
❖**Omnidirectional cameras:**



- Large field of view
- orientation independency
- Image of the entire environment acquired without rotation

Considerable evidence indicates that honeybees memorizes visual snapshots and correlates them with the currently perceived image to aim goal reaching

- Use of ensembles (multi-net) of self-organizing maps (SOM)
- Test & select approach to find the best performing ensemble from a set of alternatives
- Ensembles showed significant improvement over their single SOM counterparts
- Simulation of a Nomad200 mobile robot encircled evenly with 16 ultra-sonic and 16 infra-red sensors
- Comparison of the reliability results for both IEV and CEV methodologies

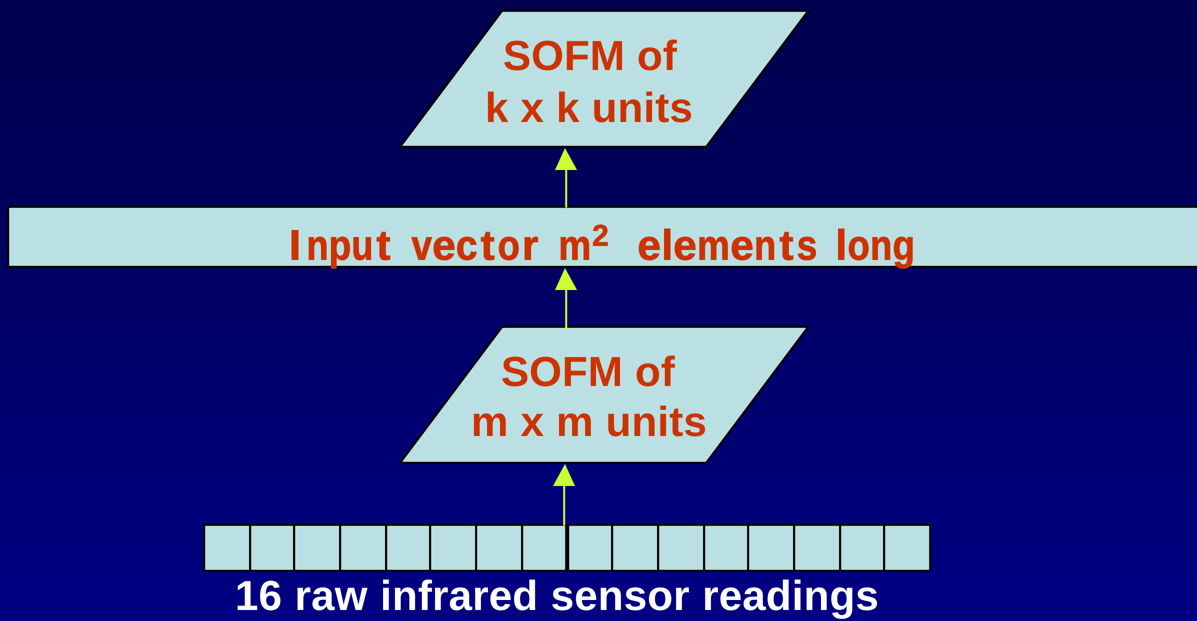


(a) *Individual Evidence Vector (IEV).* (b) *Common Evidence Vector (CEV).*

Common Evidence Vectors for Self-Organized Ensemble Localization
Gerecke U. et.al., (2003), Neurocomputing 55: 499-519

- Global Localization based on current and preceding perceptions of the world
- Topological clustering using Self-Organizing Feature Maps
- Experimental procedures with a Nomad200 mobile robot for one settled and one clattered environment.
- Disambiguation of two locations with identical perceptual signatures, if the perception precedings those two locations differ
- Episodic mapping mechanism outperforms static mapping mechanism, irrespective of experimental parameters such as bin sizes or history length
- Too much episodic mapping produces worse results than static mapping

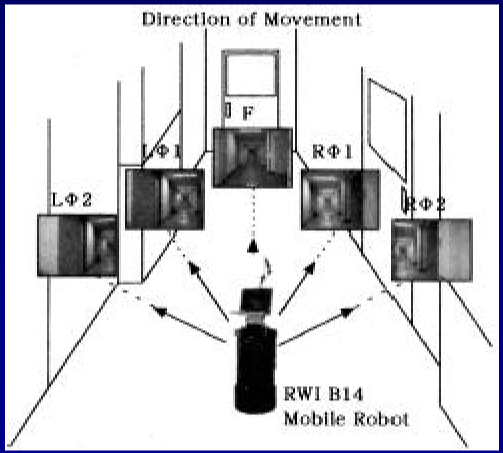
“Meaning” through Clustering by Self-Organisation
of Spatial and Temporal Information
Ulrich Nehmzow (1999) LNCS 1562, 209-229

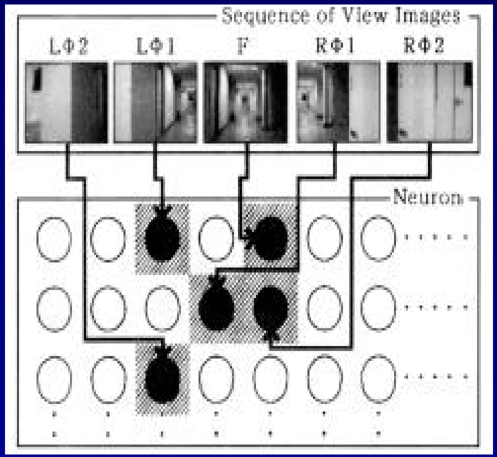


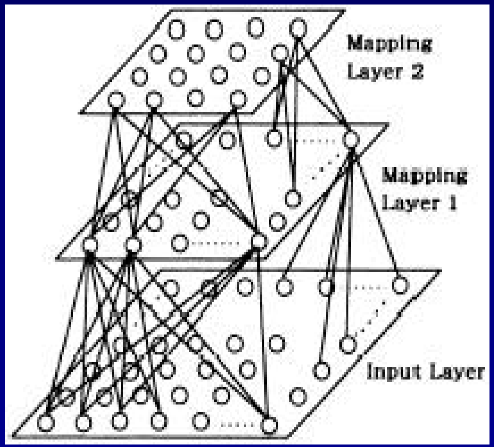
The episodic mapbuilding mechanism:
First SOM layer clusters current sensory perception
Second SOM layer clusters the last t perceptions

"Meaning" through Clustering by Self-Organisation of Spatial and Temporal Information
Ulrich Nehmzow (1999) LNCS 1562, 209-229

- Location Estimation generated from Landscape changes detected via viewpoint shifts
- Position information acquired from Hierarchical SOM
- Effectiveness for practical use confirmed in a hospital with a convalescent ward



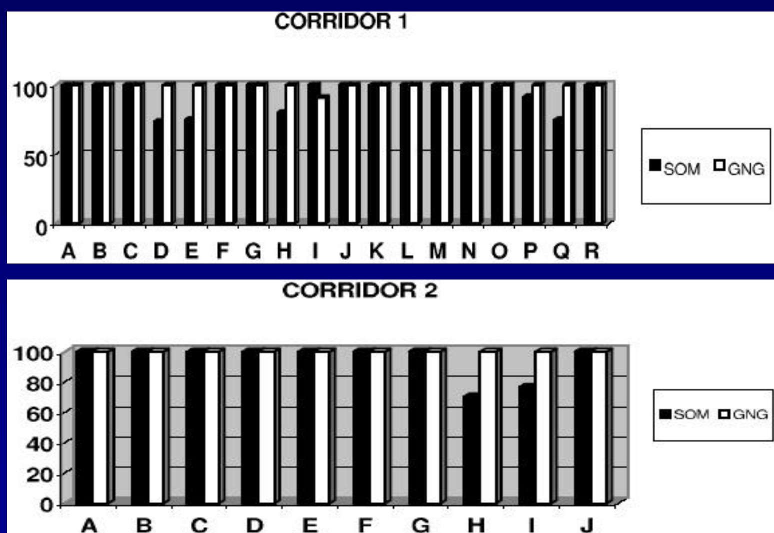




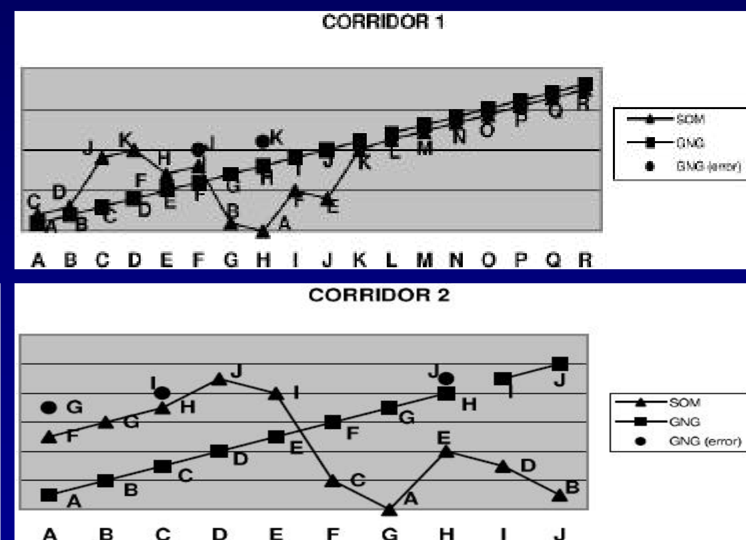
Acquisition of World Images and Self-Localization Estimation Using Viewing Image Sequences

Hirokazu Madokoro et.al. Syst Comp Jpn, Vol 34, No 1, (2003)

- Application of the topology preserving capabilities of two different self-organizing maps
- GNG adapts better than network with predefined topology (SOM)
- SOM nodes does not reflect the sequence of different zones in which The corridor is divided
- GNG forms always a perfectly topology preserving mapping



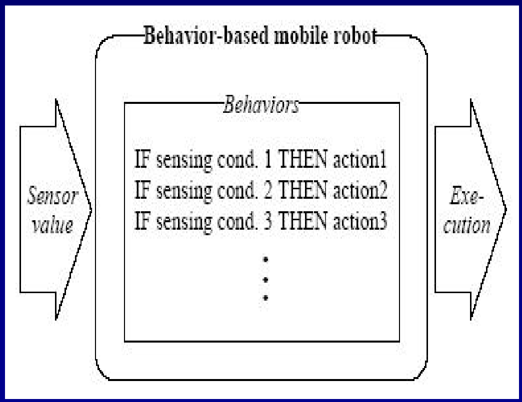
Comparison of the percentage of recognition



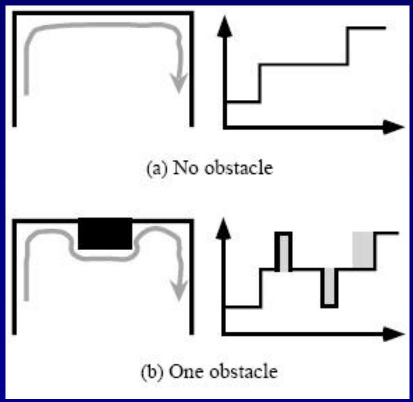
Comparison of the topology preservation

Self-organizing maps versus Growing Neural Gas in a Robotic Application
Paola Baldassarri et.al. (2003) LNCS 2687, pp. 201-208

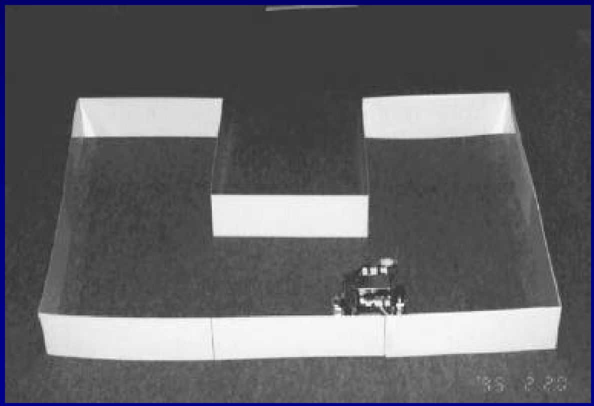
- Robot models environments using not sensed data, but sequences of executed actions
  - Robot is behavior based (does wall –following in enclosures)
  - Sequences of actions obtained and transformed into real-value vectors
  - Vectors inputted to SOM.
  - Method independent of a start point using partial action sequence
- Shapes of rooms restricted to rectangles



Behavior Based Robot



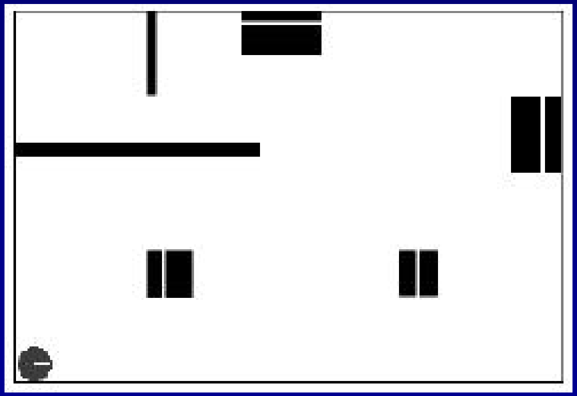
BI transformation



Experimental environment

Recognizing Environments from action sequences Using self-organizing maps
S. Yamada (2002) Applied Soft Computing 4, 35-47

- Addressing the problem of perceptual aliasing
  - First, a SOM provides a shortlist of candidate locations
  - Second, robot moves a short distance (using relative odometry)
  - All of current candidate grid locations that are consistent to a move from previous candidate location gives the evidence score
- Studies run on a realistic simulation of a nomad200 robot
- Methods of evaluation (accuracy determined by the distance between neighbor grid points)
  - Static testing of the SOM
  - Testing the reliability of localization



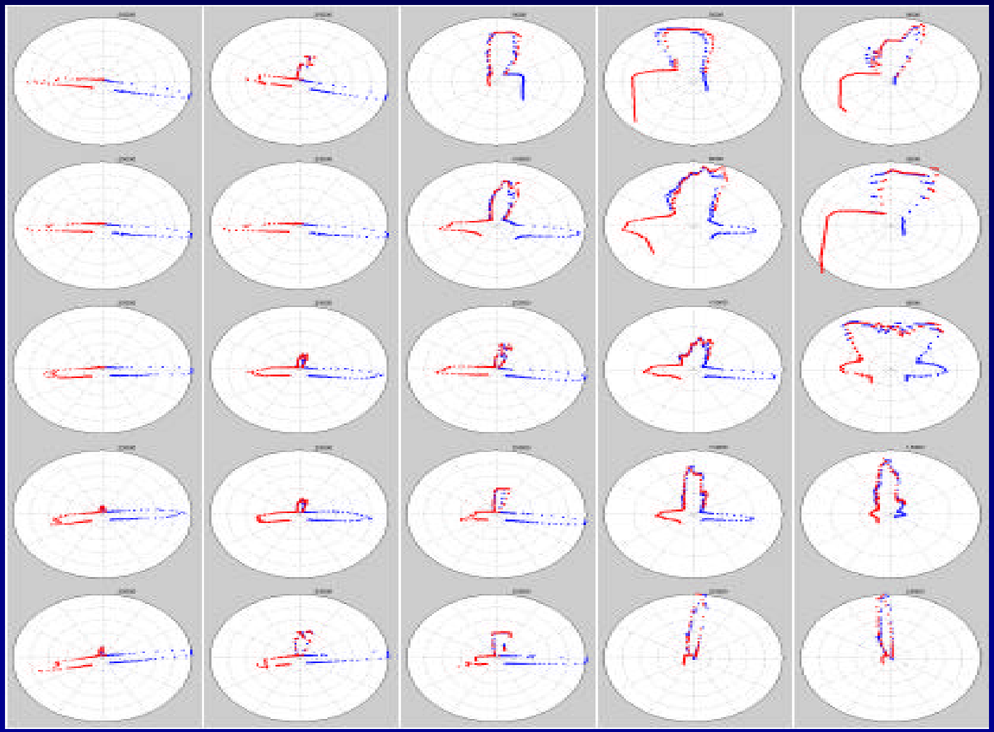
The robot environment

Radius of Uncertainty	Static Test	Localization
5	54.6%	46.2%
8	79.3%	71.0%
10	84.5%	79.2%
12	87.1%	84.8%
15	89.0%	88.8%
20	90.5%	92.0%
30	91.9%	93.4%
40	92.3%	93.6%
50	93.2%	94.4%
100	96.4%	96.8%
Nearest Grid Point	63.2%	51.0%

Percentage correct for static and localization reliability

Quick and Dirty Localization for a lost robot
Uwe Gerecke & Noel Sharkey (CIRA-99)

SOM trained with range-finder images to represent sensor views
Problem: Similar images make SOM to over-fit data



SOM Weight Vectors as sensor Views.

Toward Learning the Causal Layer of the Spatial Semantic Hierarchy using SOMs

Jefferson Provost and **Patrick Beeson** and **Benjamin J. Kuipers**