

The International Summer School
July 2010

Fuzzy - neural robot navigation

Anton Vitko

*Faculty of Electrical Engineering and Information Technology
Bratislava*

1

OUTLINE

- Introduction
- Ways of navigation
- Elements of fuzzy systems, neural networks and information fusion
- Classical *versus* behavioural approach to robot navigation
- Simulation and experimental results

2

Impressive development of computer science, sensors control, communication, smart materials and MEMS created conditions for building

autonomous intelligent robots,
i.e. those which navigate and operate
in a real world and in real time
on the basis of
multimodal information
delivered by sensors of different modalities

The task is extraordinary complex as to the real world is dynamic and unknown

3

Two essential reasons for studying mobile robots:

1. Pragmatic reason

Robots are becoming substitutes of humans, extensions of human capabilities, helpers, friends...

4

Robotic rover - Sojourner, launched inside Pathfinder to Mars
in Dec 1996 and landed in July 1997.
It was the **first semi-autonomous vehicle** on the Martian surface.

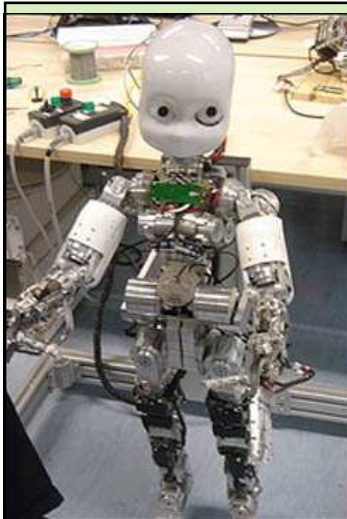


2. Epistemologic (cognitive) reason

Robots are models of what we know about the human mind, the body, and interactions with environment.

Robots are proofs of our conjectures about knowing and acting.

6



i-CUB robot, the humanoid baby-robot designed as part of the **RobotCub** project

The main focus is to implement biologically sound models of cognition in humanoid robots.

The aim is two-fold :

- furthering our understanding of brain functions
- realizing robot controllers that can learn and adapt from their mistakes

7

Autonomous robot is an instantiation of the intelligent system.

Its functionality relies on

sensors
through which the robot
grasps a consistent and coherent view
of **its own state**
and **state of environment**,
i.e. a context

8

General cognitive capabilities

perception (observation) - **modifies cognition**

cognition (reasoning, decision making) – **modifies actions and adapts perceptions**

Due to these (dual) capabilities the robot can actively explore the environment
by re-locating the point of observation.

9

Specific cognitive capabilities

- localisation in the environment
- collaboration with others
- goal formulation
- know where to look at and what to do
- know what will **likely** happen next
- learning from results
- representing knowledge for sharing with others
- self-organization
- planning
- gathering new incentives and skills through interactions with environment
- image recognition, and the more...

10

Sensing modalities

major :

seeing
touching
tasting
smelling (olfaction)
hearing

specific:

detection of tiny amounts of invisible radiation
detection of movements that are too small or fast for human eye to see
kinesthesia - body movement and balance
proprioception (the perception of body awareness)
and still others

11

Intelligent robots cannot be restricted
to those employig
particular constituents
of **soft computing techniques**
(fuzzy logic, neural networks, genetic (memetic)
algorithms and probabilistic reasoning)
as it is sometimes done.

Hallmarks of intelligent machines are
smart interaction and **pro-activeness**

12

NAVIGATION

13

From Latin: **navigare** = sailing, cruising
a voyage over the sea

Dead reckoning (*navigation by calculation*). The current position and orientation is deduced on the basis of the previous position, motion direction, speed and time.

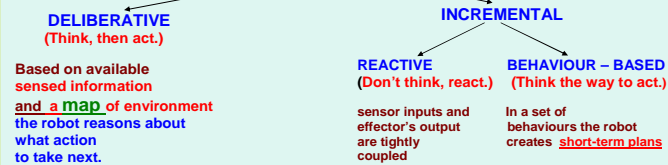
„Dead“ reckoning or „Ded“ (deduced) reckoning ?

Odometry (from Greek *hodos* = lengths, *metron* = to measure) - a kind of dead reckoning where the length is measured by counting revolutions of wheels

Visual odometry – robot position is deduced from the sequence of images.

Inertial navigation - the robot position is calculated ¹⁴ by integration of acceleration.

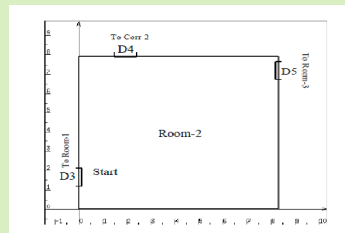
Ways of navigation:



Global navigation : Robot position is determined w.r.t.
absolute reference system

Local navigation : Robot position is determined w.r.t.
other objects on the basis of interactions with them

16



Geometric map - represents the objects in accordance with their **absolute position**

The area has its own coordinate system and metric information

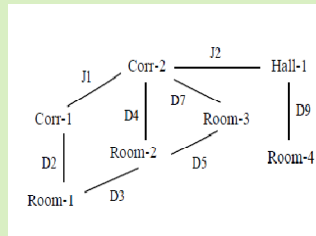
Topologic map - is a graph. It captures the structure of the space **in terms of connectivity and adjacency**

The nodes represent places which are in some way significant for navigation.

The edges represent a way the robot may move from one place to another.

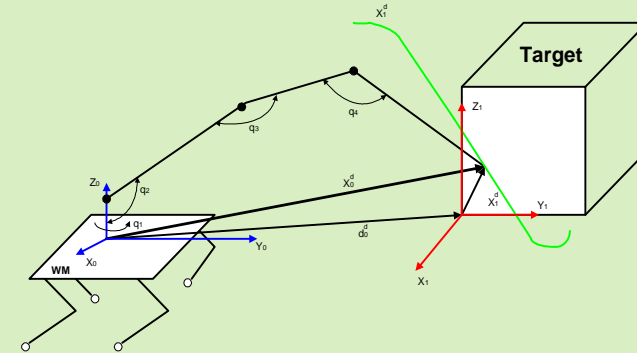
Some additional information is often used to employ a correct navigation strategy.

E.g., the planner should **distinguish between a corridor-like space** that can be traversed by wall following, and an **open space** that should be traversed by dead reckoning.



17

Navigation may include robot positioning w.r.t. a target



$$x_0^d(t) = R_0^1 x_1^d + d_0^1$$

18

The map-based navigation
is successful
in well structured environments

Problem: Map matching
i.e.
finding a correspondence
between the map and real environment

19

Elements of fuzzy logic

20

Fuzzy logic deals with approximate rather than precise reasoning.

In contrast to "crisp" (classical) propositional logic,
propositions are represented with degrees of truthfulness.

For example,

the statement, today is sunny, might be 100% true if there are no clouds,
80% true if there are a few clouds, 50% true if it's hazy and 0% true if it rains all day

Caution!

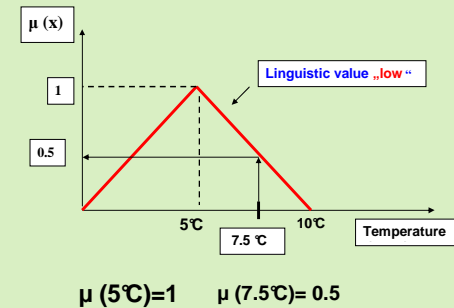
Fuzzy logic and probabilistic logic are mathematically similar – both have true values ranging between 0 and 1 – but conceptually distinct – they have different interpretations.

Fuzzy logic corresponds to "degrees of truth",
while probabilistic logic corresponds to "probability, likelihood".

They represent different models of the same real-world.

21

Linguistic value of a crisp quantity



22

Logical inference
(process of drawing conclusion)

23

Modus ponens for propositional logic

Declaration: x is A and y is B
Inference rule: if x is A and y is B then z is C
Conclusion: z is C

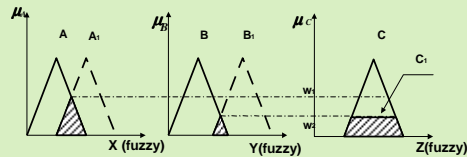
24

(Generalized) modus ponens for fuzzy inputs

Declaration: x is A_1 and y is B_1
 Rule: if x is A and y is B then z is C
 Conclusion: z is C_1

If w_1, w_2 are degrees of match between A and A_1 , and B and B_1 respectively, then $\min(w_1, w_2)$ is a degree of the rule fulfilment.

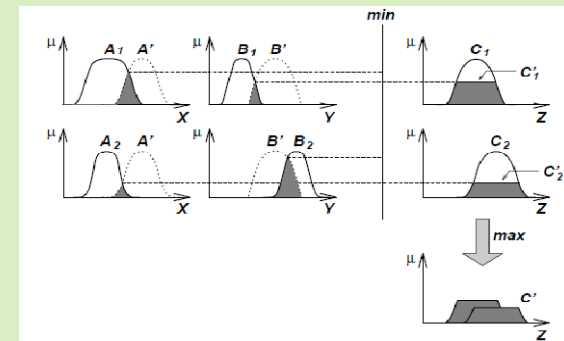
The output membership μ_{C_1} is obtained by clipping down as shown below.



25

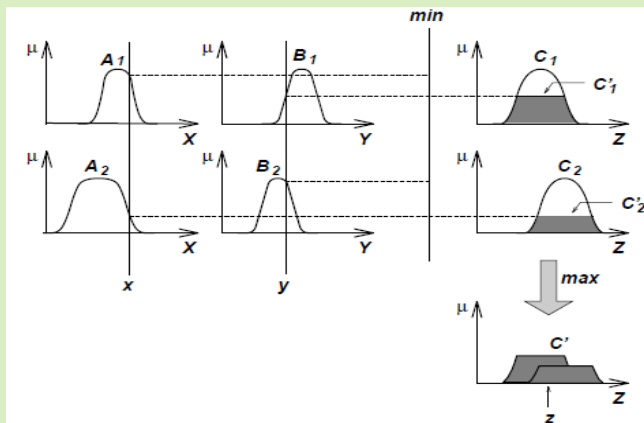
Mamdani inference – a case of two rules and fuzzy inputs and outputs

premise 1 (fact): x is A' and y is B' ,
 premise 2 (rule 1): if x is A_1 and y is B_1 then z is C_1
 premise 3 (rule 2): if x is A_2 and y is B_2 then z is C_2
 consequence (conclusion): z is C' ,

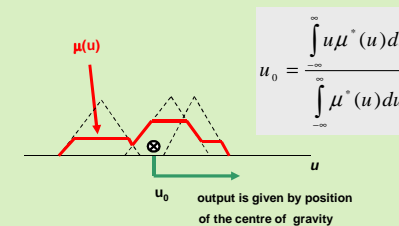


26

Mamdani inference - a case of crisp inputs

Defuzzification
(Centre of Gravity method)

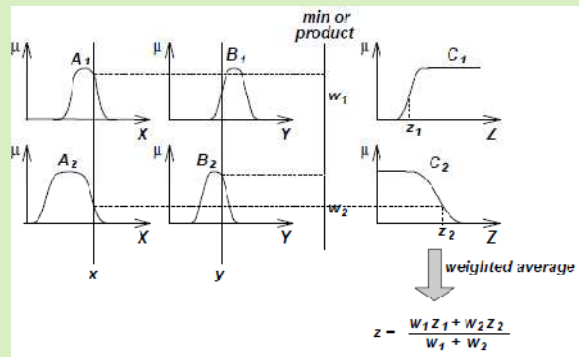
The most frequently used



28

Tsukamoto fuzzy inference - output MFs are monotonic functions.

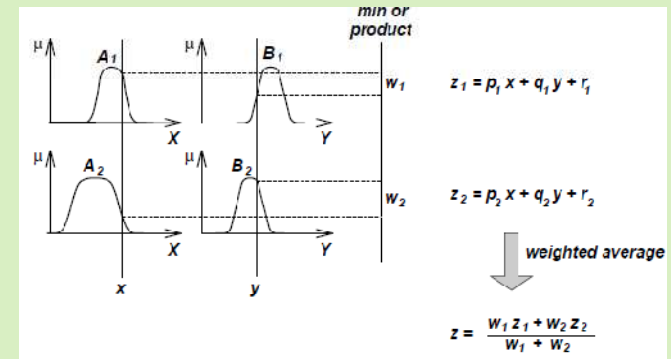
As a result output is of crisp nature.



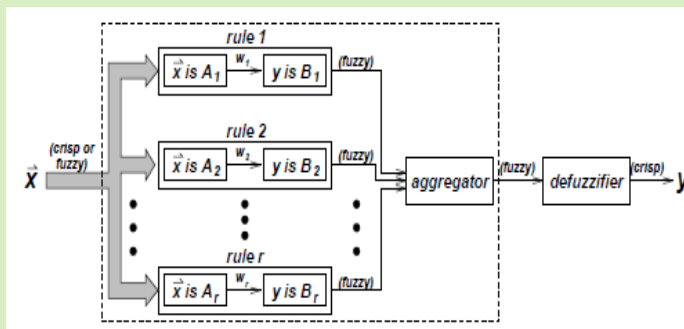
29

To avoid time consuming defuzzification, the „weighted average“ **TSK fuzzy inference** is often used

Typical rule: if x is A and y is B then $z=f(x,y)$



Fuzzy inference over multiple rules



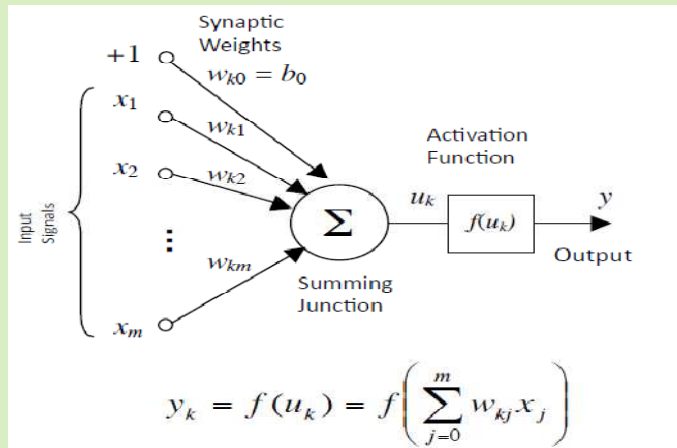
31

NEURAL NETWORKS

STRUCTURE
AND
LEARNING

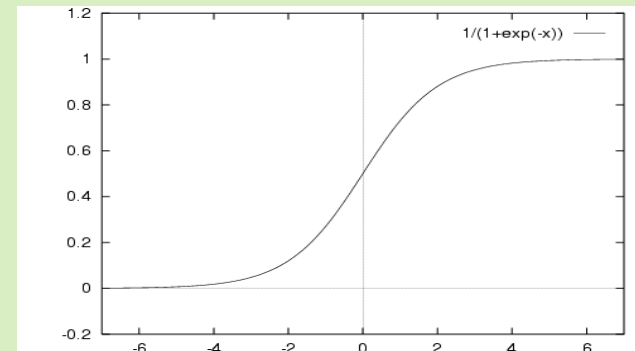
32

A single neuron

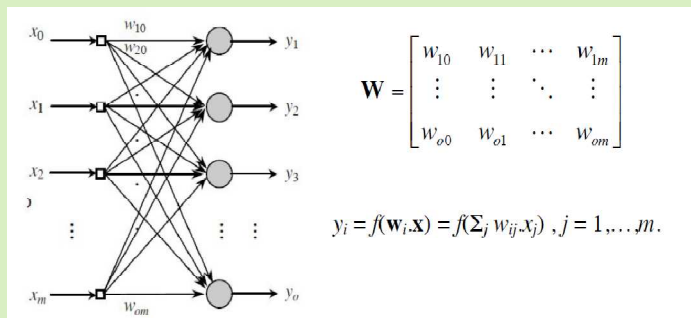


Sigmoidal activation function

$$y = f(x) = \frac{1}{1 + e^{-x}} \quad y' = y(1 - y)$$

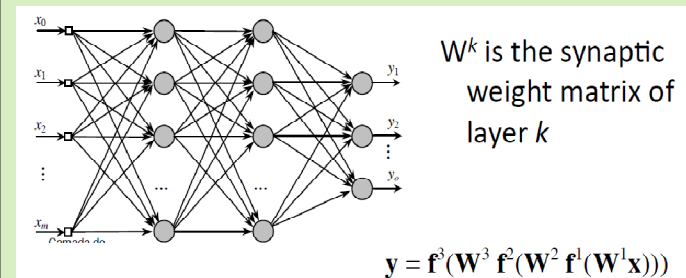


Single-layer Feedforward Network



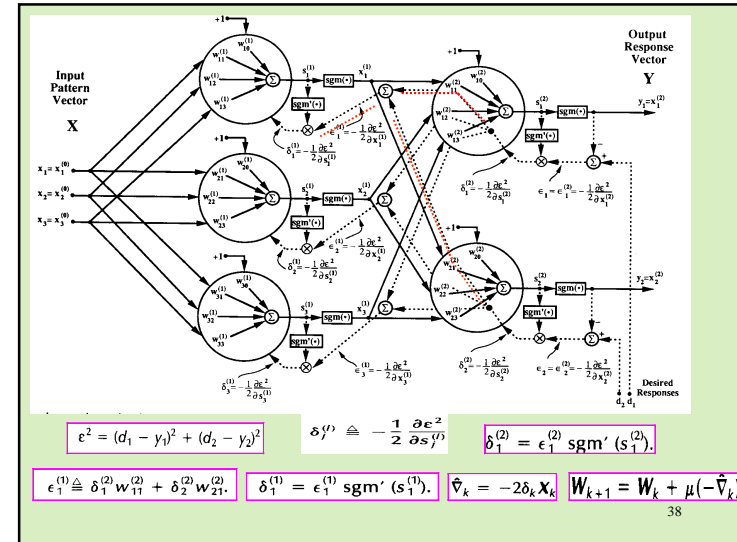
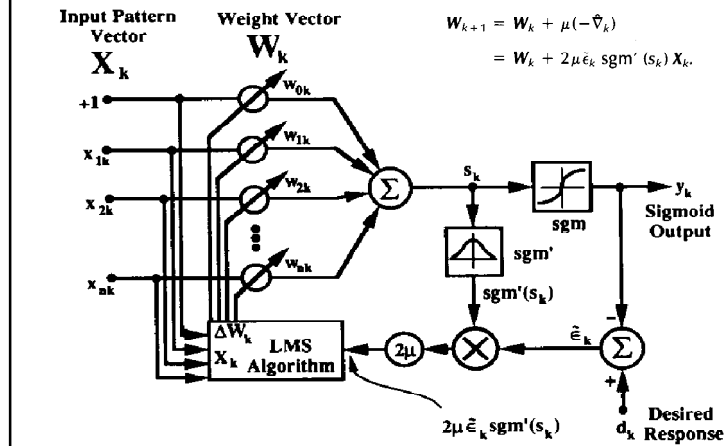
35

Multilayer Feedforward Network



36

Idea of backpropagation for a sigmoid neuron



The means of modelling and learning TSK fuzzy model is ANFIS

If x is A_1 and y is B_1 THEN $f_1 = p_1 x + q_1 y + r_1$

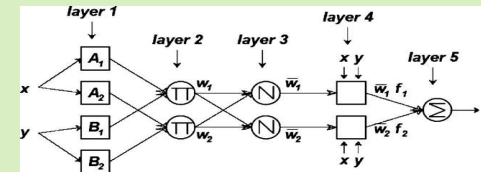
If x is A_2 and y is B_2 THEN $f_2 = p_2 x + q_2 y + r_2$

Outputs of the TSK model
are linear functions of inputs.

39

The ANFIS structure for two inputs

Layer 1 (adaptive) MFs (A_1, A_2, B_1, B_2) of the inputs (x, y)
Layer 2 (fix) evaluation of firing strength (e.g. $w_1 = w_{x1} w_{y1}$)
Layer 3 (fix) normalized firing strengths



Layer 4 (adaptive) polynomial functions f_1 and f_2 with adapt. parameters
Layer 5 (fix) f = weighted sum

$$\text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

40

	Forward Pass	Backward Pass
Premise Parameters	Fixed	Gradient Descent
Consequent Parameters	Least-squares estimator	Fixed
Signals	Node outputs	Error signals

Two passes in the hybrid learning algorithm for ANFIS.

41

**Classical
versus
behaviour – based
approach to (intelligent) navigation**

42

CLASSICAL APPROACH (GOFAI)

- Employs **explicit symbolic representation** of the environment
- **Knowledge and its representation is central to** intelligence

Control is decomposed into **functional modules** that process sensor signals in serial stages.

In particular: Perception module
Planning module
Actuator module that executes action.

43

BEHAVIOUR - BASED APPROACH

Rodney Brooks from MIT suggested to design a navigator
as a set of behaviours.

Brooks (1987):

"Planning is just a way of avoiding figuring out what to do next"

Internal model is not necessary for an agent **to act competently.**

44

BEHAVIORISM versus COGNITIVISM

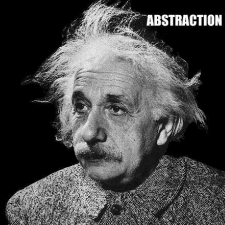
BEHAVIOURISM

COUPLED TO ENVIRONMENT
NO INTERNAL MODEL OF ENVIRONMENT
PURELY REACTIVE RESPONSE
STATELESSNESS



COGNITIVISM

UNCOUPLED FROM ENVIRONMENT
INTERNAL MODEL OF ENVIRONMENT
SYMBOLIC LOGICAL THINKING
ABSTRACTION



45

Behaviours are **basic units** for control, representation and learning.

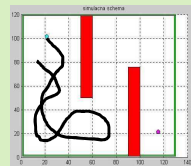
The behaviour has **emergent properties** which result from interactions.

Contrary to cognitive strategy
BB system **does not need any special system** performing **high-level cognitive** tasks.

46

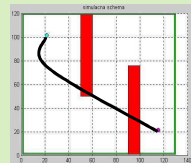
Avoiding obstacles

Robot moves freely with no specific aim, but avoids obstacles.



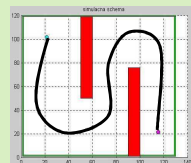
Motion toward the goal

Robot moves toward the goal without paying attention to the presence of obstacles.
The only thing of its interests is the direction to the goal.

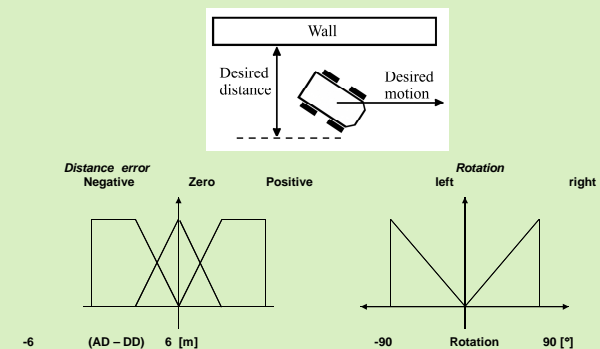


Behaviour fusion

Robot moves toward the goal and simultaneously avoids obstacles ...



Fuzzy description of the wall - following behavior



Robot is required to follow a wall at the desired distance DD , while keeping the orientation of its own body parallel to the wall.

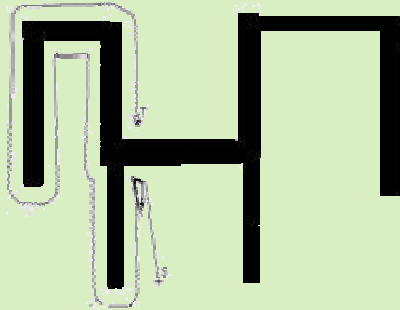
IF $(AD - DD)$ is negative THEN (Rotation is right) AND step forward

IF $(AD - DD)$ is positive THEN (Rotation is left) AND step forward

IF $(AD - DD)$ is zero THEN step forward

48

A Pure Wall-following behavior



49

AT LEAST THREE LEVELS CAN BE IDENTIFIED:

High level behaviour (a.k.o. a **task oriented** behaviour)
 - goal seeking behaviour (a blend of low level behaviours)

Middle level behaviours
 - obstacle avoiding behaviour
 - inside a deadlock behaviour
 - wall - following behaviour, etc

Low level behaviour may be represented by
 - **emergency-like behaviour** (with **highest priority**).
 E.g. The sensor signal is used **to directly stop the robot** *if an obstacle appears dangerously close* and avoiding is impossible.

This is done by an **atomic action** (stop, turn by +180 degrees, etc.)

The behaviours may be easily implemented **by Neuro fuzzy learning system**.

50

IDEA OF SUBSUMPTION ARCHITECTURE heralded a fundamentally new approach to get robots more intelligent.

The **overall behaviour is typically broken down** into a set of simpler behaviours, which are loosely co-ordinated.

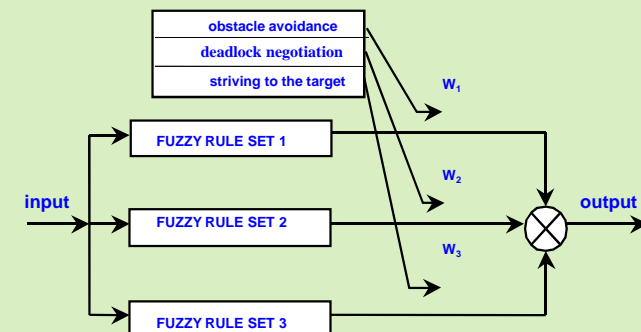
Every behaviour either **selectively assists** (with variable intensity) or **assumes** control of the subsumed behaviours.

Subsumed behaviours can be inhibited or even supersede
 By higher layers.

Contrary to hierarchical control structure, behaviours appear **concurrently**

51

Fusing (blending) behaviours in a subsumption architecture



52

Intelligent robot needs fused data

53

BENEFITS OF SENSOR FUSION

First- the robot obtains **more complex** information. This is done by fusing **complementary** information i.e. pieces of information which are mutually complemented.

For instance images from two cameras looking in different directions

Second- the robot obtains **more accurate** information. This is done by **multiple disparate sensors**, which **sense the same quantity**.

For instance, sonar and laser range sensors should sense the distance. In this case the sensors "compete" in a sense, therefore one can speak about **competitive fusion**.

54

Low levels are delineated for fusing pixels and features.

For instance, **if grey values** of neighbouring pixels are above a given threshold the AND filter is true.

Features are patterns occurring in data
for instance
mean values, correlations, variances, etc.

The low-level fusion uses **Kalman filter**
as a typical representative

55

HIGH LEVEL FUSION – a.k.o. DECISION MAKING

High level fusion **combines propositions**.
Each proposition is accompanied with its **certainty value (score)**,
expressing a **measure of truthfulness**.

Examples of propositions

$Z_{i,e}$ = there is a cube "i" in the robot's environment "e"

$Z_{i,c}$ = object "i" belongs to the cluster "c"

$Z_{d,\alpha}$ = at the angle "α" there is an obstacle at the distance "d"

Means of the high-level fusion:

- Probabilistic means (Bayesian statistics)
- Dempster-Shafer theory of evidence
- Theory of fuzzy sets and fuzzy inference

56

Higher levels are occupied by more sophisticated procedures of

notion identification and notion interpretation

i.e.
identification of **what was observed ?**
and
interpretation of **what it means to have observed that ?**

57

Information fusion and map building
based on

Dempster-Shafer theory of evidence

58

DEMPSTER-SHAFFER THEORY OF EVIDENCE

All independent declarations
about the state of a environment are enumerated
in a set $\Theta = \{E_1, E_2, \dots, E_n\}$ - frame of discernment.

A certainty - m (*mass or basic probability assignment-bpa*) is assigned to both the solitary events (E)
and every element of
the power set – Λ .
(i.e. a set of all subsets of the frame of discernment).

59

The Dempster-Shafer inference engine searches
for the **total evidence** denoted as
"believe (E)" or **Bel (E)**
that supports the occurrence of an event E.

The search is done
by (recursive) application of the
Dempster's rule of combination

60

Dempster's rule of combination

Let two sensors S_1 and S_2 with respective bpa-s m_1 and m_2

sense the elements of $\Theta = \{E_1, E_2, \dots, E_n\}$

Then **the total belief**

(i.e. **the fused evidence supporting the occurrence of the event E**)
will be

$$\text{Bel}(E) = \frac{\sum_{\forall \{B, C\} \in \Lambda: B \cap C = E} m_1(B) \cdot m_2(C)}{1 - \sum_{\forall \{B, C\} \in \Lambda: B \cap C = \emptyset} m_1(B) \cdot m_2(C)}$$

61

Example:

Robot divides its surroundings into a grid. Each cell has assigned a mass
– i.e. a measure of confidence of 3 possibilities "occupied", "empty" and "unknown".

Because "unknown" equals to "occupied or empty", (i.e. $U = O \vee E$) we have:

$$\text{Power set} = (\Phi, O, E, U, O \vee E, O \vee U, E \vee U, O \vee E \vee U) = (\Phi, O, E, U)$$

Let the **measures of confidence** are m_s for sensors
and m_o for old evidence (the mass m from the previous iteration)

During mapping the **robot calculates $m(O)$ for each cell** as follows:

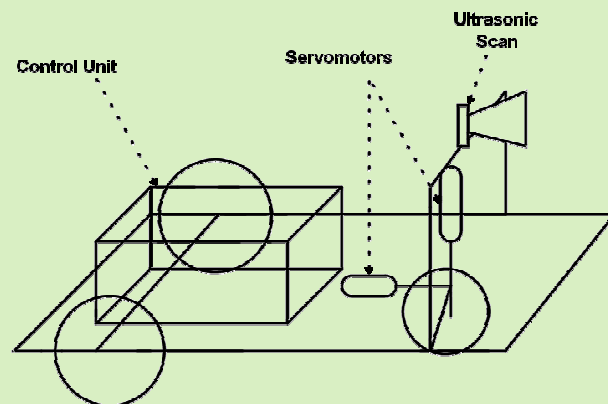
$$m(O) = \frac{m_s(O)m_o(O) + m_s(O)m_o(U) + m_s(U)m_o(O)}{1 - m_s(O)m_o(E) - m_s(E)m_o(O)}$$

IF $m(O)$ is greater than a given confidence level the robot makes a point...
In this way the robot generates a free path.

Quality (of the results) depends on the sensor masses m_s

62

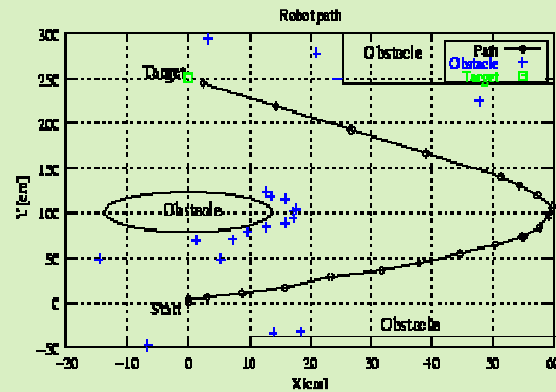
The mobile platform



63



The environment map built by the mobile platform



65

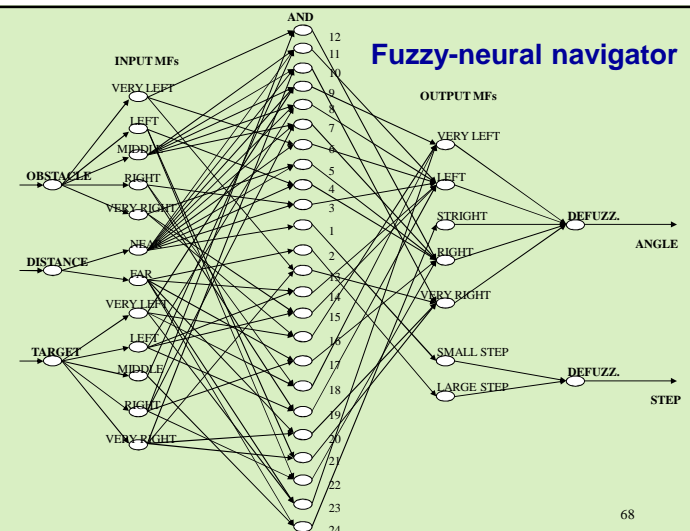
FUZZY- NEURAL NAVIGATION

66

An assortment of fuzzy rules

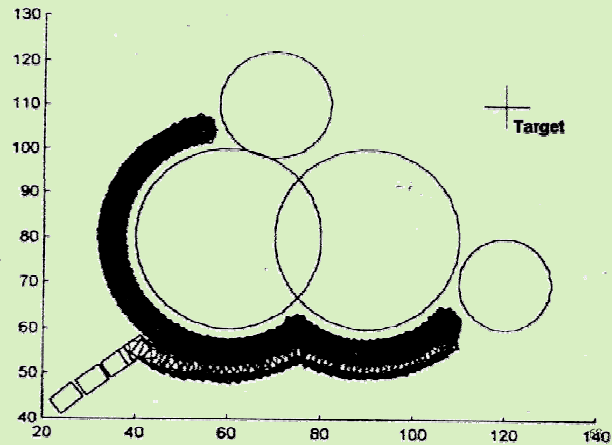
1. If distance is near **then** step is small
2. If distance is far **then** step is large
3. If obstacle is right **and** distance is far **then** turn left
- .
- .
- .
- 23.
- 24.

67

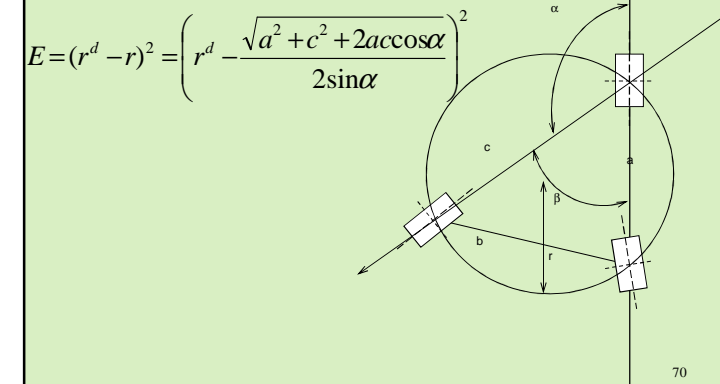


68

Robot motion before learning



Optimality criterion for unsupervised learning



Adaptation error

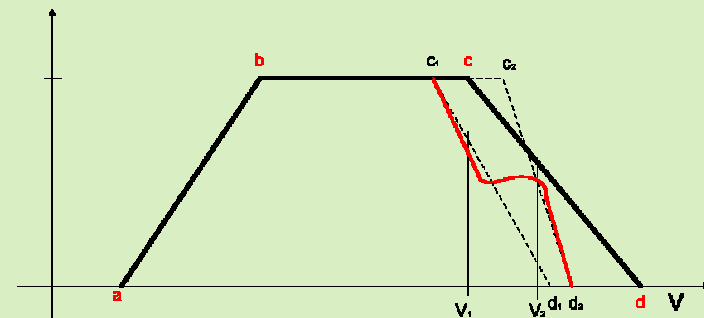
$$E = (r^d - r)^2 = \left(r^d - \frac{\sqrt{a^2 + c^2 + 2accos\alpha}}{2\sin\alpha} \right)^2$$

$$\varepsilon = \left(\frac{\partial E}{\partial \alpha} \right)_{\alpha^*}$$

Adaptation error ε was
backpropagated towards the
input layer

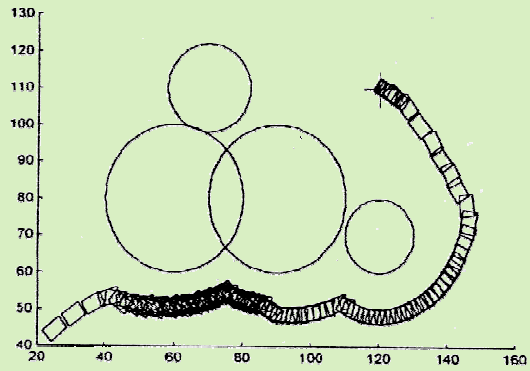
71

Modification of a trapezoidal MFs during learning



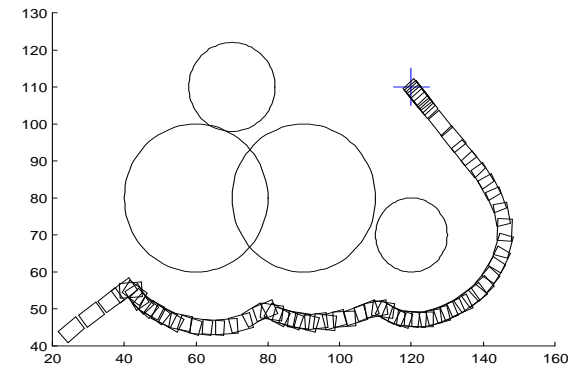
72

After the rough learning

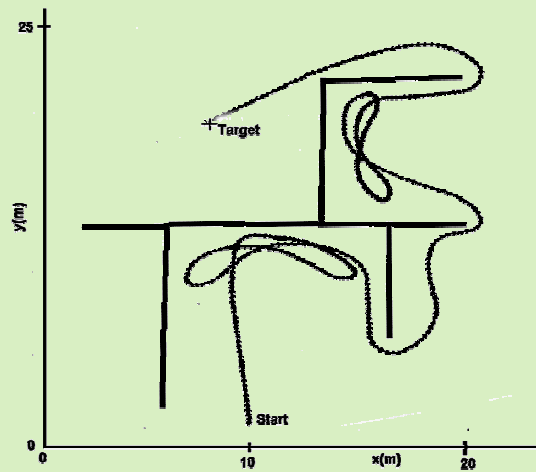


73

After the fine learning

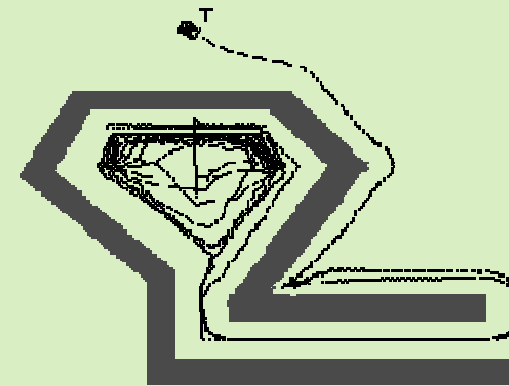


74



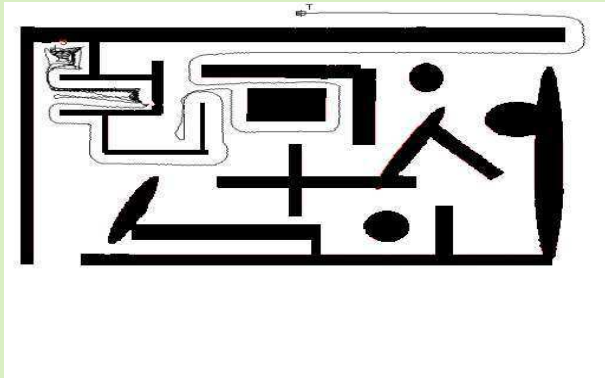
75

Behaviour in a hollow space



76

Navigation in a more complex environment



**THANK YOU
FOR YOUR ATTENTION**

78