Martin Štěpnička, Radek Valášek, Ondřej Polakovič

Dynamic Robot Control Based on the Methods of Fuzzy Logic

University of Ostrava

Institute for research and applications of fuzzy modeling

Ostrava, Czech Republic

Introduction

L.A. Zadeh - FUZZY SETS

Vagueness ⇢ human language ⇢ expert knowledge

Knowledge ⇢ fuzzy rules ⇢ **FRB**

Applications: decision making, information retrieval, data mining, **fuzzy control**

Main goal: Robot self-control and driving using some methods of fuzzy methods (Fuzzy Rule Base interpretation, inference mechanism)

FRB - Fuzzy Rule Base

consist of n fuzzy rules

$$\text{IF } x \text{ IS } \mathcal{A}_i \text{ THEN } y \text{ IS } \mathcal{F}_i \tag{1}$$

$\mathcal{A}_i$, $\mathcal{F}_i$ - linguistic expressions represented by fuzzy sets $\mathbf{A}_i$, $\mathbf{F}_i$,

Key issue:

- **Interpretation of FRB** (Inference mechanism
  Perception-based logical deduction (V. Novák), T-S systems
  (T. Takagi - M. Sugeno, etc.
  Disjunctive, Conjuctive normal form.

- **Identification of Model** (Construction of FRB)

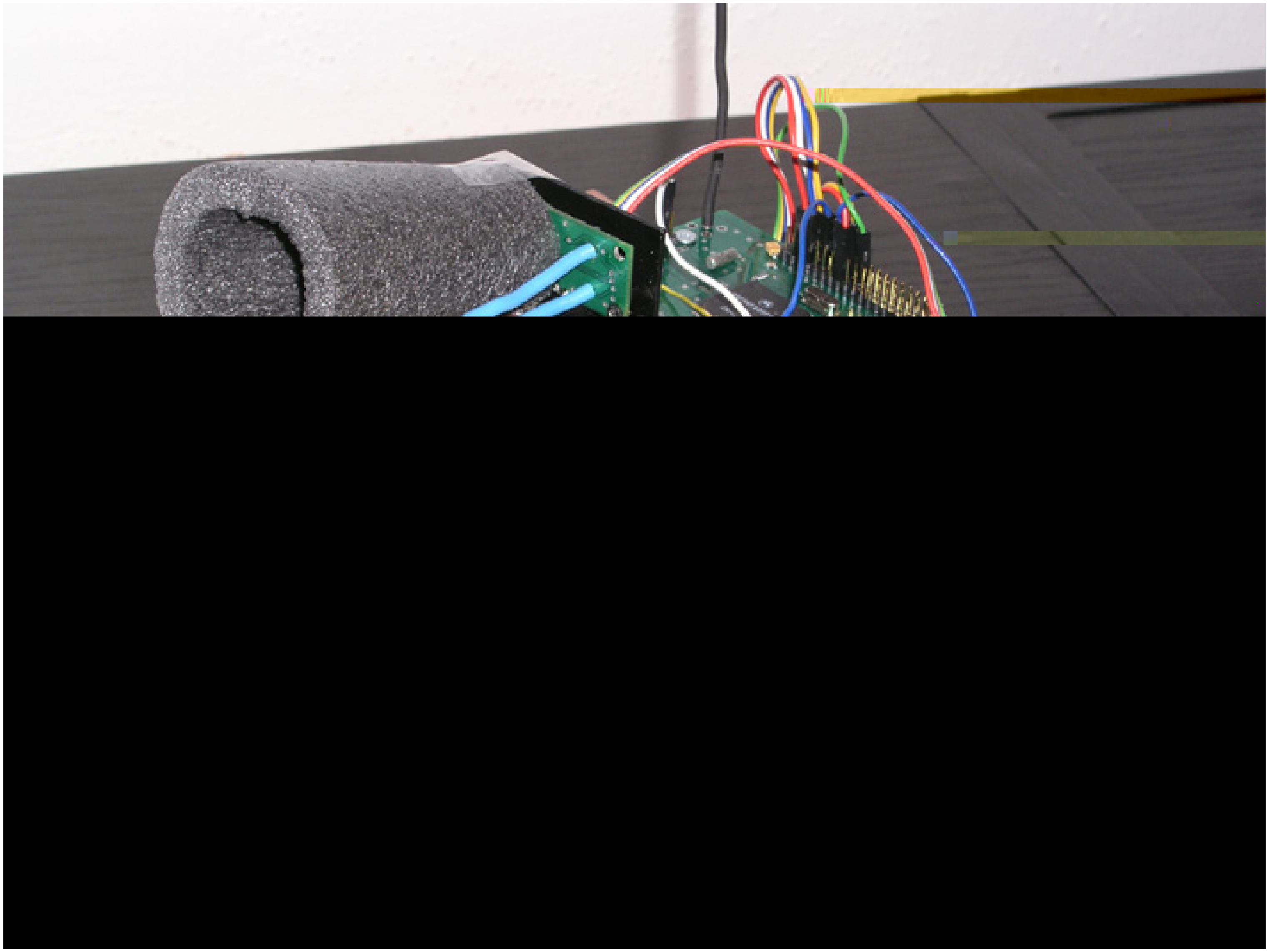
Dynamic Robot Control

- Task - Robot rides through the corridor without any accident.

- Vague definition of the task.

- INPUTS:
  1) E - relative distance from the center of a corridor
  2) ΔE - change of relative distance

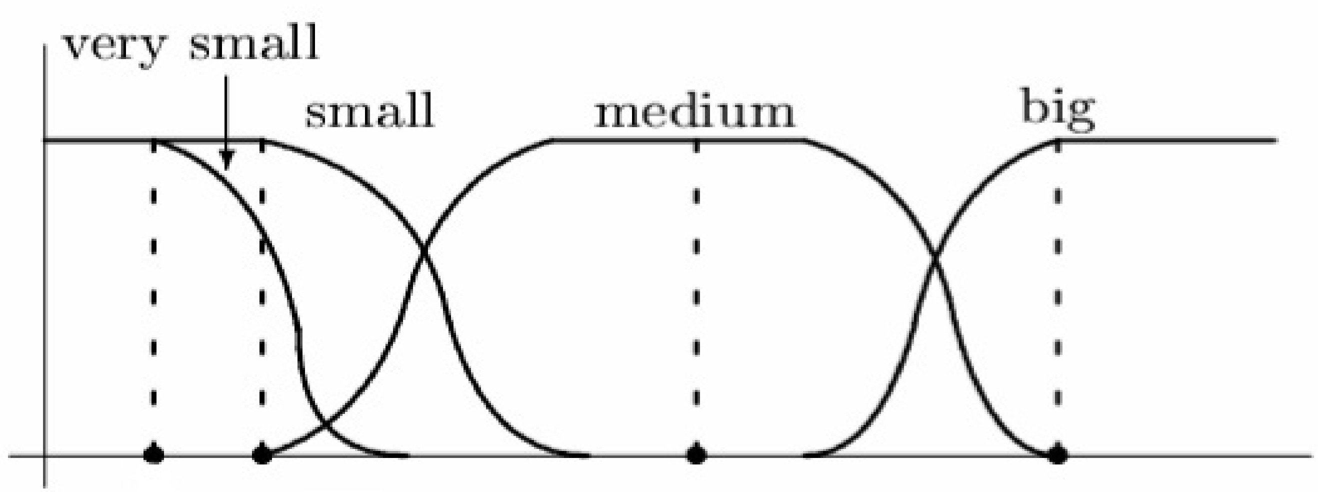
- OUTPUT (control action):
  Turning radius



Purely Linguistic Model

Inference mechanism: Perception Based Logical Deduction (V. Novák)

- uses Lukasiewicz implication
- rules are not joined by conjunction
- only one rule is active



Construction of Model

- Expert approach (testing and tuning)

- Universal PD FRB (testing and tuning)

- Linguistic learning (LFLC2000)
  (Analysis of consistency and redundancy of rules in FRB)

- All 3 approaches leads to successively control the robot driving.

- Behaviour was not smooth enough.

Fuzzy Approximation Approach

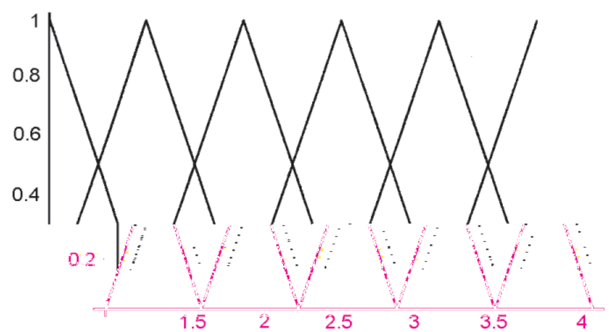
Fuzzy Transform (I. Perfilieva)

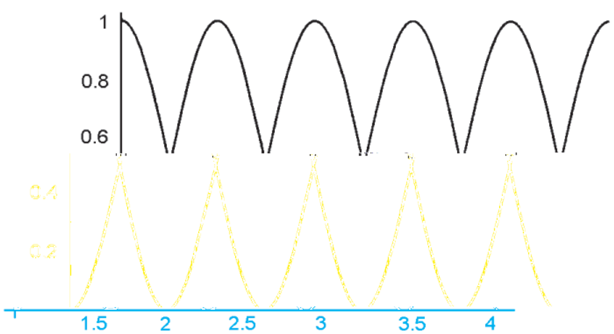
$X = [a, b]$; $f : X \to Y$ - continuous (control) function

Antecedents - fuzzy sets $\mathbf{A}_i$: $X \to [0, 1]$, $i = 1, \ldots, n$

basis functions (fuzzy partition of X)

$$\sum_{i=1}^{n} \mathbf{A}_i(x) = 1, \quad \text{for all } x \in X$$





Fuzzy Transform of continuous f

Respective consequents - reals F_i, $i = 1, \ldots, n$

$$F_i = \frac{\int_a^b \mathbf{A}_i(x) f(x) dx}{\int_a^b \mathbf{A}_i(x) dx} \quad (2)$$

$[F_1, ..., F_n]$ - **the direct F-transform**

Interpretation is given by

$$f_n^F(x) = \sum_{i=1}^{n} \mathbf{A}_i(x) F_i \quad (3)$$

the inverse F-transform of f

Discrete Knowledge of f

Experiments $\curvearrowright$ measured (training) data $\curvearrowright$ $\begin{array}{c} (x_1, f(x_1)) \\ q\cdot \\ \cdot \\ \cdot \\ (x_k, f(x_k)) \end{array}$

$$F_i = \frac{\sum_{j=1}^{k} \mathbf{A}_i(x_j) f(x_j)}{\sum_{j=1}^{k} \mathbf{A}_i(x_j)} \quad i = 1, \ldots, n \tag{4}$$

Interpretation is given by

$$f_n^F(x) = \sum_{i=1}^{n} \mathbf{A}_i(x) F_i \tag{5}$$

Properties

- Convergence
- Computational simplicity
- Noise removing ability
- Smoothing ability
- Best approximation in integral sense
- Must cover all situations

Extension for Fuzzy Relations

Fuzzy control

Crisp (control) function $f : X \to Y$ replaced by

Fuzzy relation $\mathbf{F} : X \times Y \to [0, 1]$ (also $\mathbf{F} : X \to [0, 1]^Y$)

Formulas analogous as previous

Instead of crisp F_i - fuzzy sets $\mathbf{F}_i(y)$ are computed

Data-driven Approach

$$\text{Experiments} \curvearrowright \begin{matrix} (x_1, f(x_1)) \\ \cdot \\ \cdot \\ \cdot \\ (x_k, f(x_k)) \end{matrix} \curvearrowright \text{fuzzification} \curvearrowright \begin{matrix} (x_1, \mathbf{F}(x_1, y)) \\ \cdot \\ \cdot \\ \cdot \\ (x_k, \mathbf{F}(x_k, y)) \end{matrix}$$

$$\mathbf{F}_i(y) = \frac{\sum_{j=1}^{k} \mathbf{F}(x_j, y)\mathbf{A}_i(x_j)}{\sum_{j=1}^{k} \mathbf{A}_i(x_j)} \tag{6}$$

can be$viewedasanFRBof$n$fuzzyrules$IF x IS $\mathcal{A}_i$ THEN y IS $\mathcal{F}_i$(7)

with the following interpretation

$$\mathbf{F}_n(x, y) = \bigoplus_{i=1}^{n} (\mathbf{A}_i(x) \odot \mathbf{F}_i(y)) \tag{8}$$

$\oplus$ - Łukasiewicz t-conorm, $\odot$ - product t-norm

The *additive interpretation* of an FRB

Additional Expert Knowledge

Learning - the system must *learn* all possible situation

Huge mass of experiments

Even that might not be sufficient

Fuzzy transform can be helpful ...

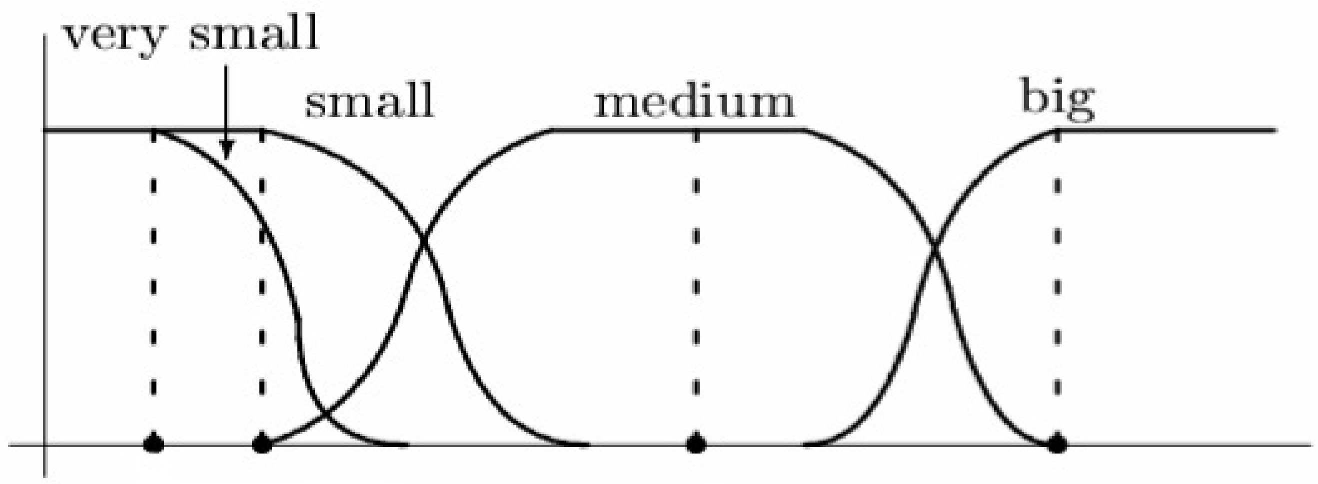
Reasonable number of experiments $\dashrightarrow$ additive FRB

Testing an automatically generated FRB $\dashrightarrow$ observing

Not sufficiently learned situations $\dashrightarrow$ **expert knowledge**

Linguistically $\mathbf{F}(x_j, y) \underset{\sim}{\subseteq} Y$ for x_j, $j = k+1, \ldots, k+r$

V. Novák:



$$\begin{array}{ccccc}
(x_1, f(x_1)) & & (x_1, \mathbf{F}(x_1, y)) & & (x_1, \mathbf{F}(x_1, y)) \\
\vdots & \curvearrowright & \vdots & \curvearrowright & \vdots \\
(x_k, f(x_k)) & & (x_k, \mathbf{F}(x_k, y)) & & (x_k, \mathbf{F}(x_k, y)) \\
 & & & & (x_{k+1}, \mathbf{F}(x_k + 1, y)) \\
 & & & & \vdots \\
 & & & & (x_{k+r}, \mathbf{F}(x_{k+r}, y))
\end{array}$$

Original consequents $\mathbf{F}_i$ are modified (recomputed)

$$\mathbf{F}_i(y) = \frac{\sum_{j=1}^{k+r} \mathbf{A}_i(x_j)\mathbf{F}(x_j, y)}{\sum_{j=1}^{k+r} \mathbf{A}_i(x_j)}$$

$\mathbf{F}_i$ - aggregate **experimental** and **expert** type of information

Results - Videos

- Without additional knowledge
- With some "extremaly" rules