

Computational Intelligence

Winter Term 2017/18

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- Approximate Reasoning
- Fuzzy Control

So far:

- p: IF X is A THEN Y is B

$$\rightarrow R(x, y) = \text{Imp}(A(x), B(y))$$

rule as relation; fuzzy implication

- rule: IF X is A THEN Y is B
- fact: $X \text{ is } A'$
- conclusion: $Y \text{ is } B'$

$$\rightarrow B'(y) = \sup_{x \in X} t(A'(x), R(x, y))$$

composition rule of inference

Thus:

- $B'(y) = \sup_{x \in X} t(A'(x), \text{Imp}(A(x), B(y)))$

given : fuzzy rule
input : fuzzy set A'
output : fuzzy set B'

here:

$$A'(x) = \begin{cases} 1 & \text{for } x = x_0 \\ 0 & \text{otherwise} \end{cases} \quad \text{crisp input!}$$

$$B'(y) = \sup_{x \in X} t(A'(x), \text{Imp}(A(x), B(y)))$$

$$= \begin{cases} \sup_{x \neq x_0} t(0, \text{Imp}(A(x), B(y))) & \text{for } x \neq x_0 \\ t(1, \text{Imp}(A(x_0), B(y))) & \text{for } x = x_0 \end{cases}$$

$$= \begin{cases} 0 & \text{for } x \neq x_0 & \text{since } t(0, a) = 0 \\ \text{Imp}(A(x_0), B(y)) & \text{for } x = x_0 & \text{since } t(a, 1) = a \end{cases}$$

Lemma:

- a) $t(a, 1) = a$
- b) $t(a, b) \leq \min \{ a, b \}$
- c) $t(0, a) = 0$

Proof:

ad a) Identical to axiom 1 of t-norms.

ad b) From monotonicity (axiom 2) follows for $b \leq 1$, that $t(a, b) \leq t(a, 1) = a$.
 Commutativity (axiom 3) and monotonicity lead in case of $a \leq 1$ to $t(a, b) = t(b, a) \leq t(b, 1) = b$. Thus, $t(a, b)$ is less than or equal to a as well as b , which in turn implies $t(a, b) \leq \min\{ a, b \}$.

ad c) From b) follows $0 \leq t(0, a) \leq \min \{ 0, a \} = 0$ and therefore $t(0, a) = 0$. ■

by a)



Multiple rules:

IF X is A_1 , THEN Y is B_1	$\rightarrow R_1(x, y) = \text{Imp}_1(A_1(x), B_1(y))$
IF X is A_2 , THEN Y is B_2	$\rightarrow R_2(x, y) = \text{Imp}_2(A_2(x), B_2(y))$
IF X is A_3 , THEN Y is B_3	$\rightarrow R_3(x, y) = \text{Imp}_3(A_3(x), B_3(y))$
...	...
IF X is A_n , THEN Y is B_n	$\rightarrow R_n(x, y) = \text{Imp}_n(A_n(x), B_n(y))$
X is A'	
<hr/>	
Y is B'	

Multiple rules for crisp input: x_0 is given

$B_1'(y) = \text{Imp}_1(A_1(x_0), B_1(y))$	}	aggregation of rules or local inferences necessary!
...		
$B_n'(y) = \text{Imp}_n(A_n(x_0), B_n(y))$		

aggregate! $\Rightarrow B'(y) = \text{aggr}\{ B_1'(y), \dots, B_n'(y) \}$, where $\text{aggr} = \begin{cases} \min \\ \max \end{cases}$

FITA: "First inference, then aggregate!"

1. Each rule of the form **IF X is A_k THEN Y is B_k** must be transformed by an appropriate fuzzy implication $\text{Imp}_k(\cdot, \cdot)$ to a relation R_k :
 $R_k(x, y) = \text{Imp}_k(A_k(x), B_k(y))$.
2. Determine $B_k'(y) = R_k(x, y) \circ A'(x)$ for all $k = 1, \dots, n$ (local inference).
3. Aggregate to $B'(y) = \beta(B_1'(y), \dots, B_n'(y))$.

FATI: "First aggregate, then inference!"

1. Each rule of the form **IF X is A_k THEN Y is B_k** must be transformed by an appropriate fuzzy implication $\text{Imp}_k(\cdot, \cdot)$ to a relation R_k :
 $R_k(x, y) = \text{Imp}_k(A_k(x), B_k(y))$.
2. Aggregate R_1, \dots, R_n to a **superrelation** with aggregating function $\alpha(\cdot)$:
 $R(x, y) = \alpha(R_1(x, y), \dots, R_n(x, y))$.
3. Determine $B'(y) = R(x, y) \circ A'(x)$ w.r.t. superrelation (inference).

1. Which principle is better? FITA or FATI?

2. Equivalence of FITA and FATI ?

FITA: $B'(y) = \beta(B_1'(y), \dots, B_n'(y))$
 $= \beta(R_1(x, y) \circ A'(x), \dots, R_n(x, y) \circ A'(x))$

FATI: $B'(y) = R(x, y) \circ A'(x)$
 $= \alpha(R_1(x, y), \dots, R_n(x, y)) \circ A'(x)$

special case:

$$A'(x) = \begin{cases} 1 & \text{for } x = x_0 \\ 0 & \text{otherwise} \end{cases}$$

crisp input!

On the equivalence of FITA and FATI:

FITA:

$$B'(y) = \beta(B_1'(y), \dots, B_n'(y))$$

$$= \beta(\text{Imp}_1(A_1(x_0), B_1(y)), \dots, \text{Imp}_n(A_n(x_0), B_n(y)))$$

FATI:

$$B'(y) = R(x, y) \circ A'(x)$$

$$= \sup_{x \in X} t(A'(x), R(x, y)) \quad (\text{from now: special case})$$

$$= R(x_0, y)$$

$$= \alpha(\text{Imp}_1(A_1(x_0), B_1(y)), \dots, \text{Imp}_n(A_n(x_0), B_n(y)))$$

evidently: sup-t-composition with arbitrary t-norm and $\alpha(\cdot) = \beta(\cdot)$

• **AND-connected premises**

IF $X_1 = A_{11}$ AND $X_2 = A_{12}$ AND ... AND $X_m = A_{1m}$ THEN $Y = B_1$
 ...
 IF $X_n = A_{n1}$ AND $X_2 = A_{n2}$ AND ... AND $X_m = A_{nm}$ THEN $Y = B_n$

reduce to single premise for each rule k:

$$A_k(x_1, \dots, x_m) = \min \{ A_{k1}(x_1), A_{k2}(x_2), \dots, A_{km}(x_m) \} \quad \text{or in general: t-norm}$$

• **OR-connected premises**

IF $X_1 = A_{11}$ OR $X_2 = A_{12}$ OR ... OR $X_m = A_{1m}$ THEN $Y = B_1$
 ...
 IF $X_n = A_{n1}$ OR $X_2 = A_{n2}$ OR ... OR $X_m = A_{nm}$ THEN $Y = B_n$

reduce to single premise for each rule k:

$$A_k(x_1, \dots, x_m) = \max \{ A_{k1}(x_1), A_{k2}(x_2), \dots, A_{km}(x_m) \} \quad \text{or in general: s-norm}$$

important:

- if rules of the form **IF X is A THEN Y is B** interpreted as logical implication
 $\Rightarrow R(x, y) = \text{Imp}(A(x), B(y))$ makes sense
- we obtain: $B'(y) = \sup_{x \in X} t(A'(x), R(x, y))$
 \Rightarrow the worse the match of premise $A'(x)$, the larger is the fuzzy set $B'(y)$
 \Rightarrow follows immediately from axiom 1: $a \leq b$ implies $\text{Imp}(a, z) \geq \text{Imp}(b, z)$

interpretation of output set $B'(y)$:

- $B'(y)$ is the set of values that are still possible
- each rule leads to an additional restriction of the values that are still possible
 \Rightarrow resulting fuzzy sets $B'_k(y)$ obtained from single rules must be mutually intersected!
 \Rightarrow aggregation via $B'(y) = \min \{ B_1'(y), \dots, B_n'(y) \}$

important:

- if rules of the form **IF X is A THEN Y is B** are not interpreted as logical implications, then the function $\text{Fct}(\cdot)$ in

$$R(x, y) = \text{Fct}(A(x), B(y))$$

can be chosen as required for desired interpretation.

- frequent choice (especially in fuzzy control):

- $R(x, y) = \min \{ A(x), B(x) \}$ Mamdani – “implication“

- $R(x, y) = A(x) \cdot B(x)$ Larsen – “implication“

\Rightarrow of course, they are no implications but specific t-norms!

\Rightarrow thus, if relation $R(x, y)$ is given, then the *composition rule of inference*

$$B'(y) = A'(x) \circ R(x, y) = \sup_{x \in X} \min \{ A'(x), R(x, y) \}$$

still can lead to a conclusion via fuzzy logic.

example: [JM96, S. 244ff.]

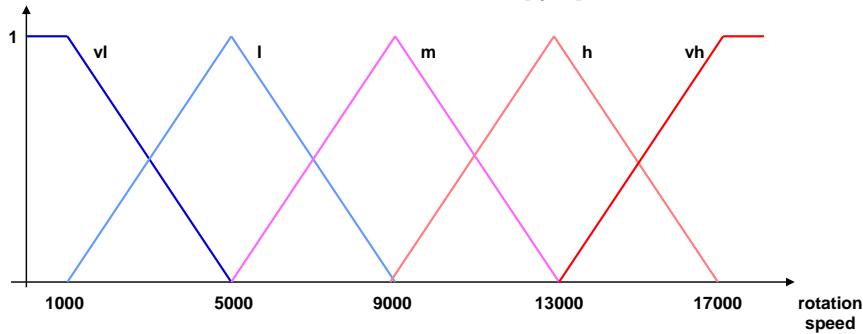
industrial drill machine → control of cooling supply

modelling

linguistic variable : **rotation speed**

linguistic terms : **very low, low, medium, high, very high**

ground set : X with $0 \leq x \leq 18000$ [rpm]



example: (continued)

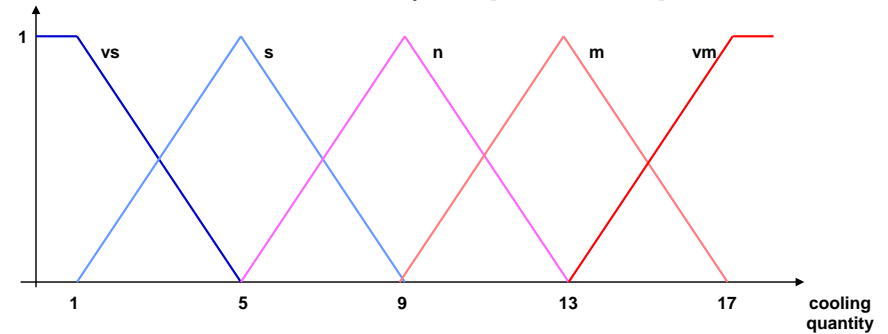
industrial drill machine → control of cooling supply

modelling

linguistic variable : **cooling quantity**

linguistic terms : **very small, small, normal, much, very much**

ground set : Y with $0 \leq y \leq 18$ [liter / time unit]



example: (continued)

industrial drill machine → control of cooling supply

rule base

IF rotation speed IS very low THEN cooling quantity IS very small

low

small

medium

normal

high

much

very high

very much

↑
sets $S_{vl}, S_l, S_m, S_h, S_{vh}$
"rotation speed"

↑
sets $C_{vs}, C_s, C_n, C_m, C_{vm}$
"cooling quantity"

example: (continued)

industrial drill machine → control of cooling supply

1. **input:** crisp value $x_0 = 10000 \text{ min}^{-1}$ (not a fuzzy set!)

→ **fuzzyfication** = determine membership for each fuzzy set over X

→ yields $S' = (0, 0, \frac{3}{4}, \frac{1}{4}, 0)$ via $x \mapsto (S_{vl}(x_0), S_l(x_0), S_m(x_0), S_h(x_0), S_{vh}(x_0))$

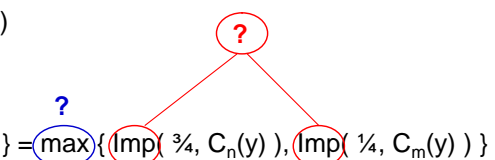
2. **FITA: locale inference** ⇒ since $\text{Imp}(0, a) = 0$ we only need to consider:

$S_m: C'_n(y) = \text{Imp}(\frac{3}{4}, C_n(y))$

$S_h: C'_m(y) = \text{Imp}(\frac{1}{4}, C_m(y))$

3. **aggregation:**

$C'(y) = \text{aggr} \{ C'_n(y), C'_m(y) \} = \text{max} \{ \text{Imp}(\frac{3}{4}, C_n(y)), \text{Imp}(\frac{1}{4}, C_m(y)) \}$



example: (continued)

industrial drill machine → control of cooling supply

$$C'(y) = \max \{ \text{Imp}(\frac{3}{4}, C_n(y)), \text{Imp}(\frac{1}{4}, C_m(y)) \}$$

in case of control task typically no logic-based interpretation:

→ max-aggregation and

→ relation $R(x,y)$ not interpreted as implication.

often: $R(x,y) = \min(a, b)$ „Mamdani controller“

thus:

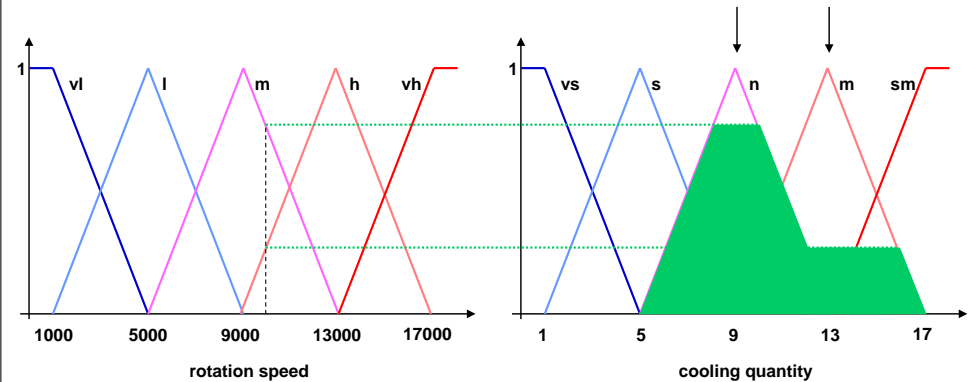
$$C'(y) = \max \{ \min \{ \frac{3}{4}, C_n(y) \}, \min \{ \frac{1}{4}, C_m(y) \} \}$$

→ graphical illustration

example: (continued)

industrial drill machine → control of cooling supply

$$C'(y) = \max \{ \min \{ \frac{3}{4}, C_n(y) \}, \min \{ \frac{1}{4}, C_m(y) \} \}, x_0 = 10000 \text{ [rpm]}$$



open and closed loop control:

affect the dynamical behavior of a system in a desired manner

• **open loop control**

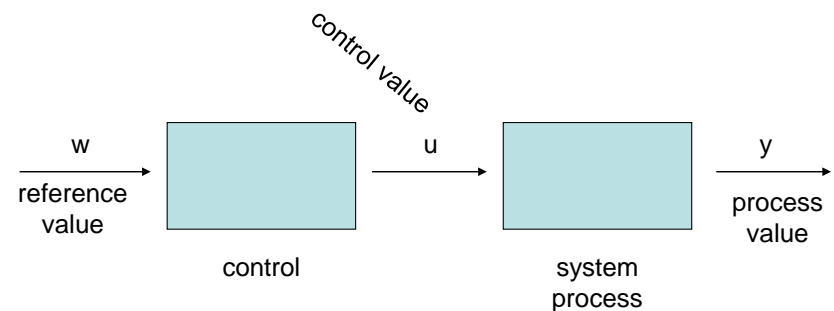
control is aware of reference values and has a model of the system
⇒ control values can be adjusted, such that process value of system is equal to reference value

problem: noise! ⇒ deviation from reference value not detected

• **closed loop control**

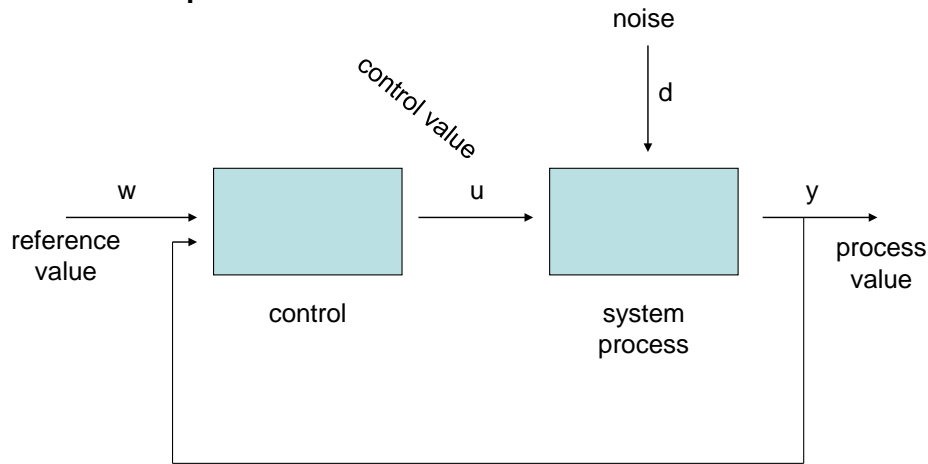
now: detection of deviations from reference value possible (by means of measurements / sensors) and new control values can take into account the amount of deviation

open loop control



assumption: undisturbed operation ⇒ process value = reference value

closed loop control



control deviation = reference value – process value

required:

model of system / process

→ as differential equations or difference equations (DEs)

→ well developed theory available

so, why fuzzy control?

- there exists no process model in form of DEs etc. (operator/human being has realized control by hand)
- process with high-dimensional nonlinearities → no classic methods available
- control goals are vaguely formulated („soft“ changing gears in cars)

fuzzy description of control behavior

IF X is A_1 , THEN Y is B_1
 IF X is A_2 , THEN Y is B_2
 IF X is A_3 , THEN Y is B_3
 ...
 IF X is A_n , THEN Y is B_n
 X is A'

} similar to approximative reasoning

but fact A' is not a fuzzy set but a crisp input
 → actually, it is the current process value

fuzzy controller executes inference step
 → yields fuzzy output set $B'(y)$

but crisp control value required for the process / system
 → defuzzification (= “condense” fuzzy set to crisp value)

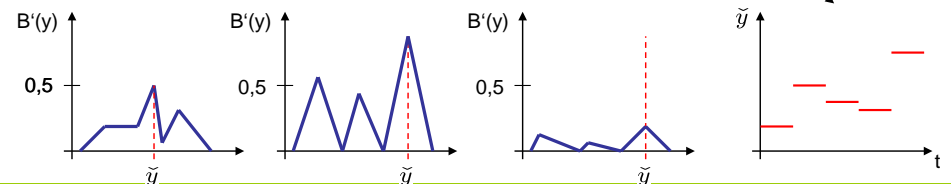
defuzzification

Def: rule k active $\Leftrightarrow A_k(x_0) > 0$

• maximum method

- only active rule with largest activation level is taken into account
 → suitable for pattern recognition / classification
 → decision for a single alternative among finitely many alternatives
- selection independent from activation level of rule (0.05 vs. 0.95)
- if used for control: incontinuous curve of output values (leaps)

$\tilde{y} = \operatorname{argmax} B'(y)$



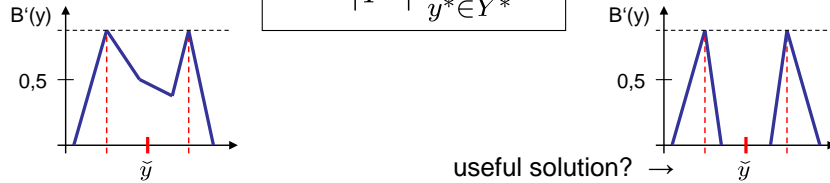
defuzzification

$$Y^* = \{ y \in Y: B'(y) = \text{hgt}(B') \}$$

• maximum mean value method

- all active rules with largest activation level are taken into account
 - interpolations possible, but need not be useful
 - obviously, only useful for neighboring rules with max. activation
- selection independent from activation level of rule (0.05 vs. 0.95)
- if used in control: incontinuous curve of output values (leaps)

$$\tilde{y} = \frac{1}{|Y^*|} \sum_{y^* \in Y^*} y^*$$



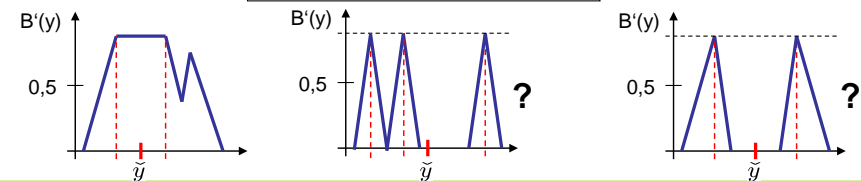
defuzzification

$$Y^* = \{ y \in Y: B'(y) = \text{hgt}(B') \}$$

• center-of-maxima method (COM)

- only **extreme** active rules with largest activation level are taken into account
 - interpolations possible, but need not be useful
 - obviously, only useful for neighboring rules with max. activation level
- selection independent from activation level of rule (0.05 vs. 0.95)
- in case of control: incontinuous curve of output values (leaps)

$$\tilde{y} = \frac{\inf Y^* + \sup Y^*}{2}$$



defuzzification

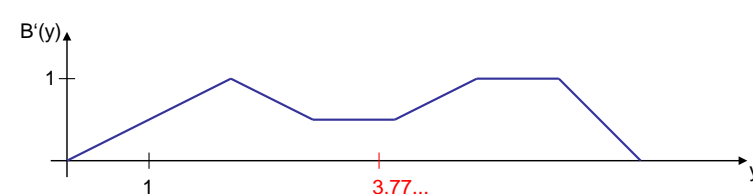
• Center of Gravity (COG)

- all active rules are taken into account
 - but numerically expensive ...
 - borders cannot appear in output (∃ work-around)
- if only single active rule: independent from activation level
- continuous curve for output values

$$\tilde{y} = \frac{\int y \cdot B'(y) dy}{\int B'(y) dy}$$

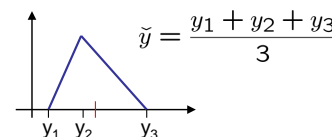
Excursion: COG

$$\tilde{y} = \frac{\int y \cdot B'(y) dy}{\int B'(y) dy}$$

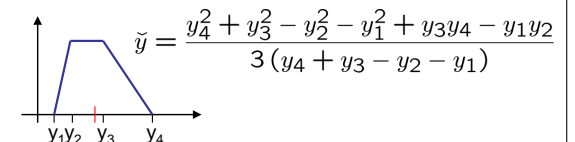


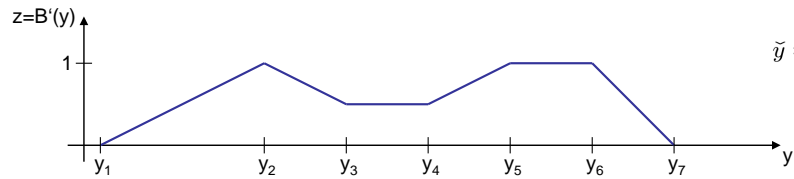
pendant in probability theory: expectation value

triangle:



trapezoid:





$$\tilde{y} = \frac{\int y \cdot B'(y) dy}{\int B'(y) dy}$$

assumption: fuzzy membership functions piecewise linear

output set B'(y) represented by sequence of points (y₁, z₁), (y₂, z₂), ..., (y_n, z_n)

⇒ area under B'(y) and weighted area can be determined additively piece by piece

⇒ linear equation z = m y + b ⇒ insert (y_i, z_i) and (y_{i+1}, z_{i+1})

⇒ yields m and b for each of the n-1 linear sections

$$\Rightarrow F_i = \int_{y_i}^{y_{i+1}} (m y + b) dy = \frac{m}{2}(y_{i+1}^2 - y_i^2) + b(y_{i+1} - y_i)$$

$$\Rightarrow G_i = \int_{y_i}^{y_{i+1}} y (m y + b) dy = \frac{m}{3}(y_{i+1}^3 - y_i^3) + \frac{b}{2}(y_{i+1}^2 - y_i^2)$$

$$\tilde{y} = \frac{\sum_i G_i}{\sum_i F_i}$$

Defuzzification

- Center of Area (COA)
 - developed as an approximation of COG
 - let \hat{y}_k be the COGs of the output sets $B'_k(y)$:

$$\tilde{y} = \frac{\sum_k A_k(x_0) \cdot \hat{y}_k}{\sum_k A_k(x_0)}$$

how to:
 assume that fuzzy sets $A_k(x)$ and $B_k(x)$ are triangles or trapezoids
 let x_0 be the crisp input value
 for each fuzzy rule "IF A_k is X THEN B_k is Y"
 determine $B'_k(y) = R(A_k(x_0), B_k(y))$, where $R(.,.)$ is the relation
 find \hat{y}_k as center of gravity of $B'_k(y)$