

Computational Intelligence

Lecture 10: Fuzzy Control II

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Fuzzy Control

Nonadaptive Fuzzy Control Trial-and-Error Approach

PID Controller Using Fuzzy Systems Fuzzy System for PID

Comparing Fuzzy Control with Conventional Control

► Similarities:

- They must address the same issues that are common to any control problem, e.g., stability and performance.
- The mathematical tools used to analyze the designed control systems are similar, because they are studying the same issues (stability, convergence, etc.) for the same kind of systems.

► Difference

- In conventional control mathematical model of the process and controllers are available. In fuzzy control, the controllers are designed using rules based on heuristics and human expertise
 - Advanced fuzzy controllers may use both heuristics and mathematical models

Fuzzy Control

- ▶ Fuzzy control is classified into
 - ▶ Nonadaptive Fuzzy Control
 - ▶ the structure and parameters of the fuzzy controller are fixed
 - ▶ Adaptive Fuzzy Control
 - ▶ The structure or/and parameters of the fuzzy controller change during realtime operation.
- ▶ Nonadaptive fuzzy control is simpler than adaptive fuzzy control
- ▶ Nonadaptive fuzzy control requires more knowledge of the process model or heuristic rules.
- ▶ Adaptive requires less information and may perform better at the cost of more complexity.

Assumption is Fuzzy Control Design

- ▶ The plant is observable and controllable: state, input, and output variables are usually available for observation and measurement or computation.
- ▶ There exists a body of knowledge comprised of a set of linguistic rules, engineering common sense, intuition, or a set of inputoutput measurements data from which rules can be extracted
- ▶ A solution exists.
- ▶ The control engineer is looking for a good enough solution, not necessarily the optimum one.
- ▶ The controller will be designed within an acceptable range of precision.

The Trial-and-Error Approach

- By using experience-based knowledge (e.g., an operating manual) and by asking the domain 'experts to answer a carefully organized questionnaire, IF-THEN rules are provided and fuzzy controllers are constructed
- Then the fuzzy controllers are tested in the real system and if the performance is not satisfactory, the rules are fine-tuned or redesigned in a number of trial-and-error cycles until the desired performance is achieved.

The Trial-and-Error Approach

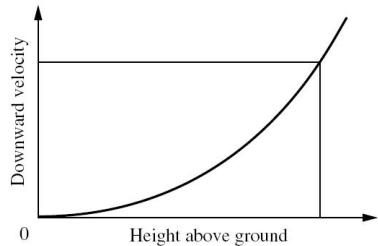
1. Analyze the real system to choose state and control variables and outputs.
 - ▶ The state variables:
 - ▶ characterize the key features of the system
 - ▶ The control variables (inputs of the plant):
 - ▶ influence the states of the system.
 - ▶ are the outputs of the fuzzy controller.
2. Partition the universe of discourse or the interval spanned by each variable into a number of fuzzy subsets, assigning each a linguistic label
 - ▶ Assign or determine a membership function for each fuzzy subset.
 - ▶ You may require to choose appropriate scaling factors for the input and output variables in order to normalize the variables to the $[0, 1]$ or the $[-1, 1]$ interval.

The Trial-and-Error Approach

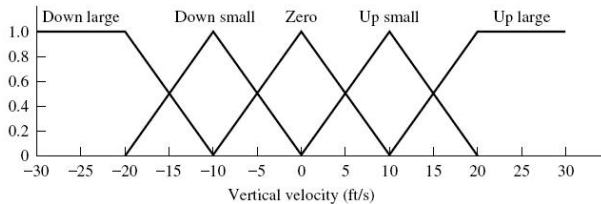
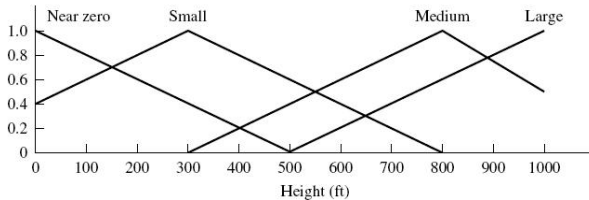
3. Derive IF-THEN rules that relate the state variables with the control variables
 - ▶ The rules are defined using
 - ▶ An introspective verbalization of human expertise like operating manual
 - ▶ the information obtained from a filled carefully organized questionnaire
4. Design the fuzzy system and test the closed-loop system with this fuzzy system as the controller
 - ▶ If the performance is not satisfactory, fine-tune or redesign the fuzzy controller by trial and error
 - ▶ repeat the procedure until achieving the desired performance

Example: AIRCRAFT LANDING CONTROL

- ▶ The desired profile is shown in Fig.
- ▶ The downward velocity is proportional to the square of the height.
 - ▶ At higher altitudes, a large downward velocity is desired.
 - ▶ As the height (altitude) diminishes, the desired downward velocity gets smaller and smaller.
 - ▶ In the limit, as the height tends to be zero, the downward velocity also goes to zero.
- ▶ The states:
 - ▶ h : height above ground
 - ▶ v : vertical velocity of the aircraft
- ▶ The control signal
 - ▶ f : force

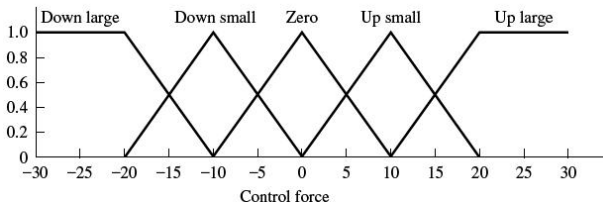


- ▶ Mass m moving with velocity v has momentum $p = mv$.
- ▶ If a force f is applied over a time interval $\Delta t \rightsquigarrow \Delta v = f \Delta t / m$
- ▶ $\Delta t = 1.0(s)$ and $m = 1.0/b \rightsquigarrow \Delta v = f$
- ▶ $\therefore v_{i+1} = v_i + f_i, \quad h_{i+1} = h_i + v_i \Delta t$
 - ▶ v_{i+1} : new velocity, v_i : old velocity
 - ▶ h_{i+1} new height, h_i old height



Membership values for control force

	Output force													
	-30	-25	-20	-15	-10	-5	0	5	10	15	20	25	30	
Up large (UL)	0	0	0	0	0	0	0	0	0	0.5	1	1	1	
Up small (US)	0	0	0	0	0	0	0	0.5	1	0.5	0	0	0	
Zero (Z)	0	0	0	0	0	0.5	1	0.5	0	0	0	0	0	
Down small (DS)	0	0	0	0.5	1	0.5	0	0	0	0	0	0	0	
Down large (DL)	1	1	1	0.5	0	0	0	0	0	0	0	0	0	

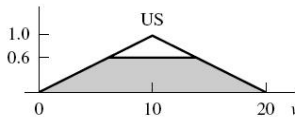
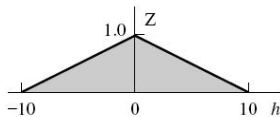


- The rules are summarized in the table

Height	Velocity				
	DL	DS	Zero	US	UL
L	Z	DS	DL	DL	DL
M	US	Z	DS	DL	DL
S	UL	US	Z	DS	DL
NZ	UL	UL	Z	DS	DS

- Let us use
 - singleton fuzzifier,
 - min inf. eng.
 - centroid defuzzifier

- ▶ Initial height, $h_0 : 1000ft$; Initial velocity, $v_0 : -20ft/s$
- ▶ $h = 1$ for L and 0.6 for M
- ▶ $v = 1$ for DL
- ▶ \therefore
 - $L(1.0) \text{ AND } DL(1.0) \Rightarrow Z$
 - $M(0.6) \text{ AND } DL(1.0) \Rightarrow US$
- ▶ Using defuzzifier: $f_0 = 5.8/b$



- ▶ $h_1 = h_0 + v_0 = 980ft$;
- ▶ $v_1 = v_0 + f_0 = -14.2ft/s$
- ▶ $h_1 = 0.96$ for L and 0.64 for M
- ▶ $v_1 = 0.58$ for DS and 0.42 for DL

▶ ∴

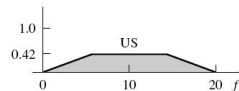
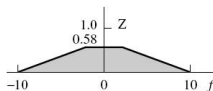
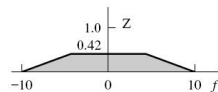
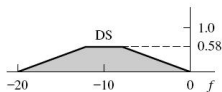
$L(0.96) \text{ AND } DS(0.58) \Rightarrow DS$

$L(0.96) \text{ AND } DL(0.42) \Rightarrow Z$

$M(0.64) \text{ AND } DS(0.58) \Rightarrow Z$

$M(0.64) \text{ AND } DL(0.42) \Rightarrow US$

- ▶ Using defuzzifier: $f_1 = -0.5lb$



- ▶ $h_2 = h_1 + v_1 = 965.8ft$;
- ▶ $v_2 = v_1 + f_1 = -14.7ft/s$
- ▶ $h = 0.93$ for L and 0.67 for M
- ▶ $v = 0.57$ for DS and 0.43 for DL

▶ ∴

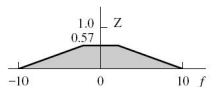
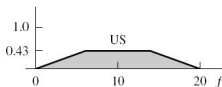
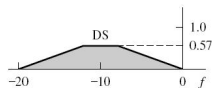
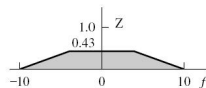
$L(0.93) \text{ AND } DL(0.43) \Rightarrow Z$

$L(0.93) \text{ AND } DS(0.57) \Rightarrow DS$

$M(0.67) \text{ AND } DL(0.43) \Rightarrow US$

$M(0.67) \text{ AND } DS(0.57) \Rightarrow Z$

- ▶ Using defuzzifier: $f_2 = -0.4lb$



Summary of four-cycle simulation results

	Cycle 0	Cycle 1	Cycle 2	Cycle 3	Cycle 4
Height, ft	1000.0	980.0	965.8	951.1	936.0
Velocity, ft/s	-20	-14.2	-14.7	-15.1	-14.8
Control force	5.8	-0.5	-0.4	0.3	

PID Controller

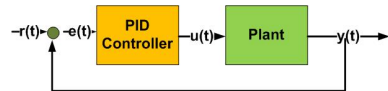
- ▶ The transfer function of a PID controller:

$$G(s) = K_p + K_i/s + K_d s$$

- ▶ $\therefore u(t) = K_p[e(t) + \frac{1}{T_i} \int_0^t e(r)dr + T_d \dot{e}(t)]$

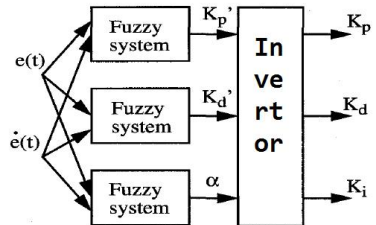
- ▶ $T_i = K_p/K_i, T_d = K_d/K_p$

- ▶ The PID gains are usually turned by experienced human experts based on some "rule of thumb."
- ▶ By using fuzzy systems, we are trying to adjust the PID gains online



Fuzzy System for PID [1]

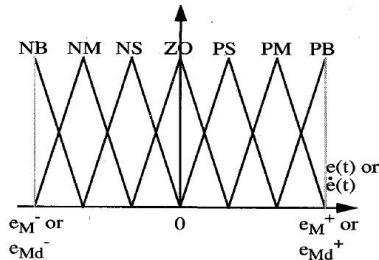
- ▶ Assume the range of PID gains:
 - ▶ $K_p \in [K_{pmax}, K_{pmin}] \subset R$
 - ▶ $K_d \in [K_{dmax}, K_{dmin}] \subset R$
- ▶ Normalize K_p and K_d to the range of $[0, 1]$
 - ▶ $K_{p'} = \frac{K_p - K_{pmin}}{K_{pmax} - K_{pmin}}$
 - ▶ $K_{d'} = \frac{K_d - K_{dmin}}{K_{dmax} - K_{dmin}}$
- ▶ Assume $T_i = \alpha T_d \rightsquigarrow K_i = \frac{K_p}{\alpha T_d} = \frac{K_p^2}{\alpha K_d}$
- ▶ Inputs of fuzzy system: $e(t), \dot{e}(t)$
- ▶ Output of fuzzy system: $K_{p'}, K_{d'}, \alpha$



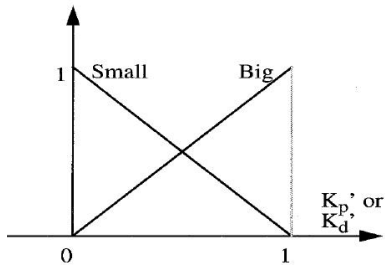
► Domain of interest:

- $e(t) \in [e_M^-, e_M^+]$
- $\dot{e}(t) \in [e_{Md}^-, e_{Md}^+]$

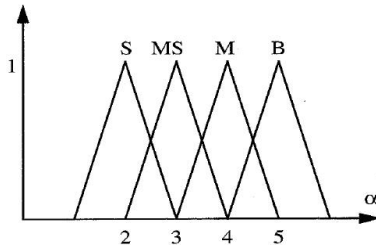
► Mem. fcn for $e(t)$ and $\dot{e}(t)$



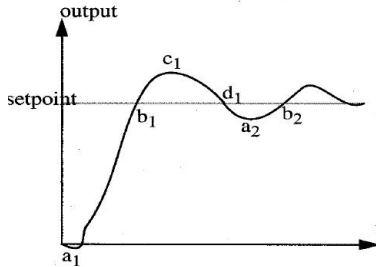
► Mem. fcn for $K_{p'}$ and $K_{d'}$



► Mem. fcn for α



- Derive the rules experimentally based on the typical step response



- For e.g., Around b_1 , a small control signal requires to avoid a large overshoot \therefore :
 - Small K_p ,
 - Large K_d ,
 - small α
- IF $e(t)$ is *ZO* and $\dot{e}(t)$ is *NB*, THEN K_p is Small, K_d is Big, α is *B*
- Find the rules for other points.

► Rules for K_p'

		$\dot{e}(t)$							
		NB	NM	NS	ZO	PS	PM	PB	
$e(t)$	NB	B	B	B	B	B	B	B	
	NM	S	B	B	B	B	B	S	
	NS	S	S	B	B	B	S	S	
	ZO	S	S	S	B	S	S	S	
	PS	S	S	B	B	B	S	S	
	PM	S	B	B	B	B	B	S	
	PB	B	B	B	B	B	B	B	

► Rules for K_d'

		$\dot{e}(t)$							
		NB	NM	NS	ZO	PS	PM	PB	
$e(t)$	NB	S	S	S	S	S	S	S	
	NM	B	B	S	S	S	B	B	
	NS	B	B	B	S	B	B	B	
	ZO	B	B	B	B	B	B	B	
	PS	B	B	B	S	B	B	B	
	PM	B	B	S	S	S	B	B	
	PB	S	S	S	S	S	S	S	

► Rules for α

		$\dot{e}(t)$							
		NB	NM	NS	ZO	PS	PM	PB	
$e(t)$	NB	2	2	2	2	2	2	2	
	NM	3	3	2	2	2	3	3	
	NS	4	3	3	2	3	3	4	
	ZO	5	4	3	3	3	4	5	
	PS	4	3	3	2	3	3	4	
	PM	3	3	2	2	2	3	3	
	PB	2	2	2	2	2	2	2	

- There are 49 rules for each output
- Consider a fuzzy system with product inference engine, singleton fuzzifier, and center average defuzzifier

$$K_{p'} = \frac{\sum_{l=1}^{49} \bar{y}_p^l \mu_{A^l}(e(t)) \mu_{B^l}(\dot{e}(t))}{\sum_{l=1}^{49} \mu_{A^l}(e(t)) \mu_{B^l}(\dot{e}(t))} \quad K_{d'} = \frac{\sum_{l=1}^{49} \bar{y}_d^l \mu_{A^l}(e(t)) \mu_{B^l}(\dot{e}(t))}{\sum_{l=1}^{49} \mu_{A^l}(e(t)) \mu_{B^l}(\dot{e}(t))}$$

$$\alpha(t) = \frac{\sum_{l=1}^{49} \bar{y}_\alpha^l \mu_{A^l}(e(t)) \mu_{B^l}(\dot{e}(t))}{\sum_{l=1}^{49} \mu_{A^l}(e(t)) \mu_{B^l}(\dot{e}(t))}$$



Z.Y. Zhao, M. Tomizuka, and S. Isaka, “Fuzzy gain scheduling of pid controllers,” *IEEE Trans. on Systems, Man, and Cybernetic* vol. 23, no 5 , pp. 1392–1398, 1993.