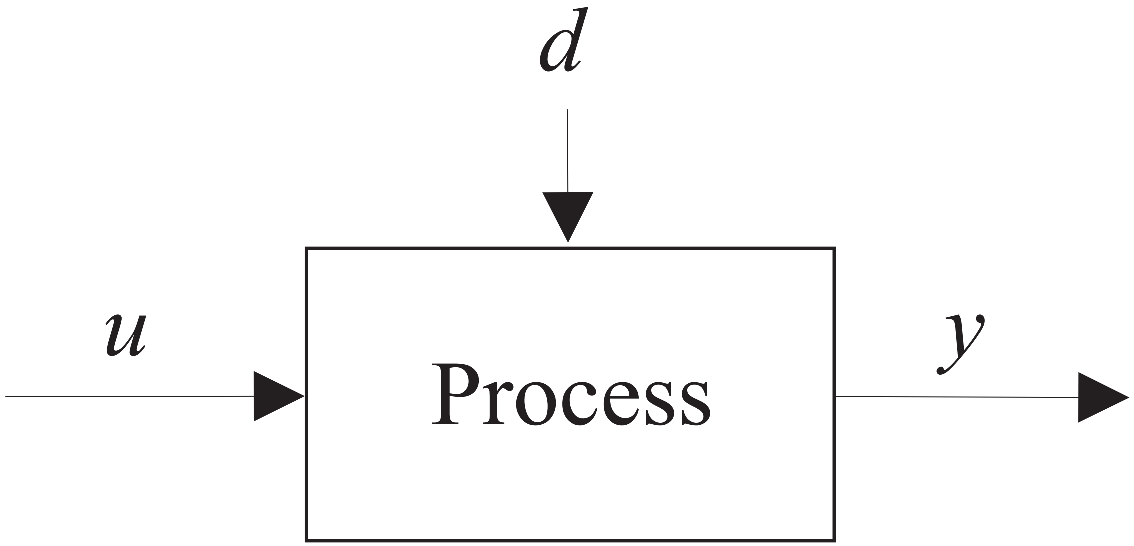
Conventional Control

A Refresher

Process to Be Controlled



y : **variable to be controlled (output)**

u : **manipulated variable (control input)**

d : **disturbance (input that cannot be influenced)**

dynamic system

Examples of "Processes"

- technical (man-made) system

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- organization (company, stock exchange)

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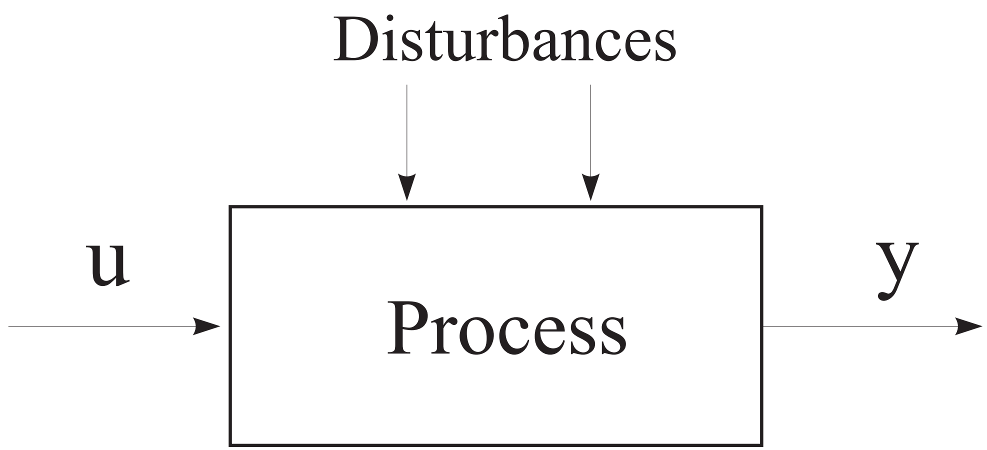
Classical Control Design



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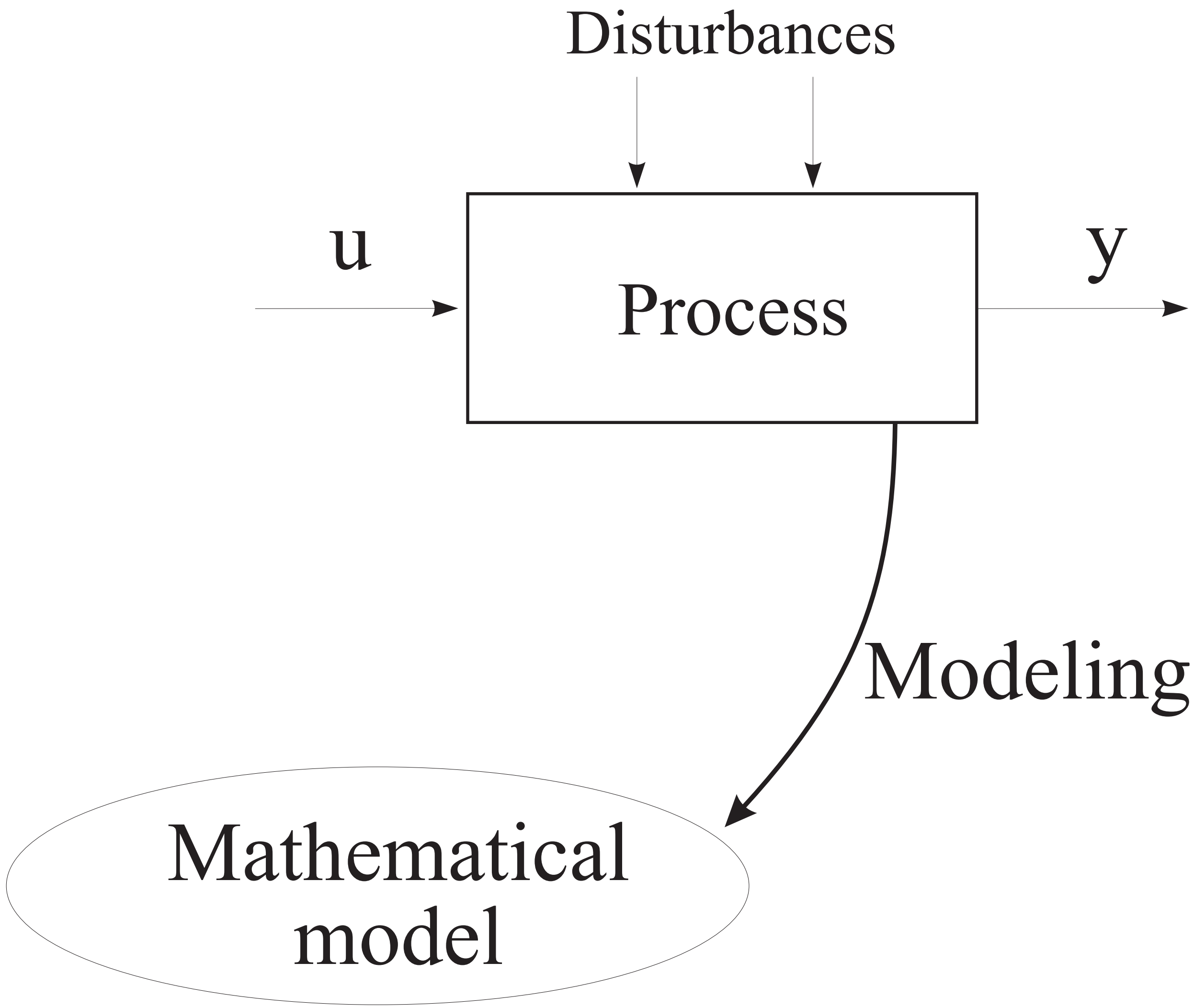

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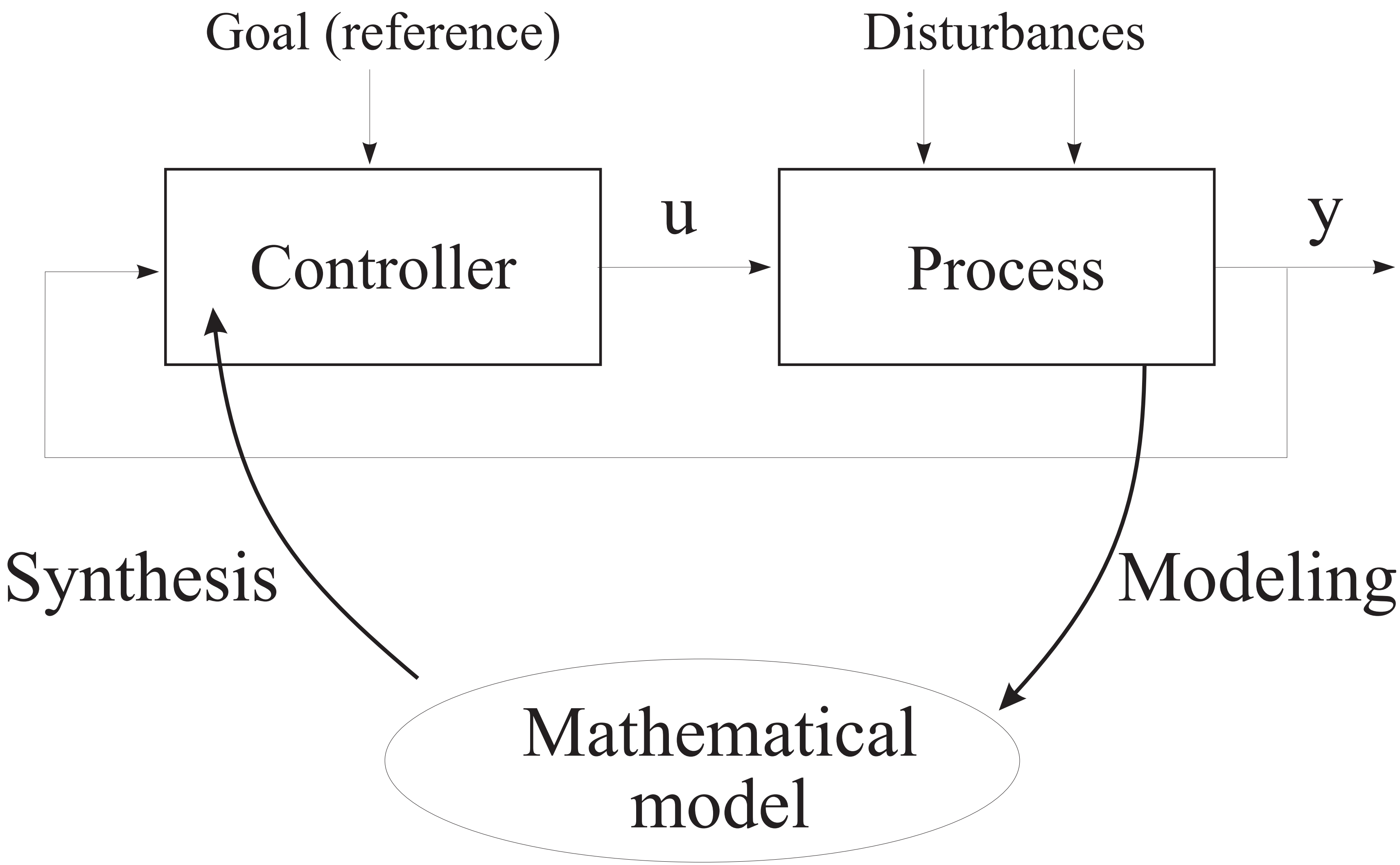

How to Obtain Models?

- physical (mechanistic) modeling
  1. first principles $\rightarrow$ differential equations (linear or nonlinear)
  2. linearization around an operating point

- system identification
  1. measure input–output data
  2. postulate model structure (linear–nonlinear)
  3. estimate model parameters from data (least squares)

Modeling of Dynamic Systems

$x(t)$ **. . . state of the system**

summarizes all history such that if we know $x(t)$ **we can predict its development in time,** $\dot{x}(t)$**, for any input** $u(t)$

linear state-space model:

$$\dot{x}(t) = Ax(t) + Bu(t)$$

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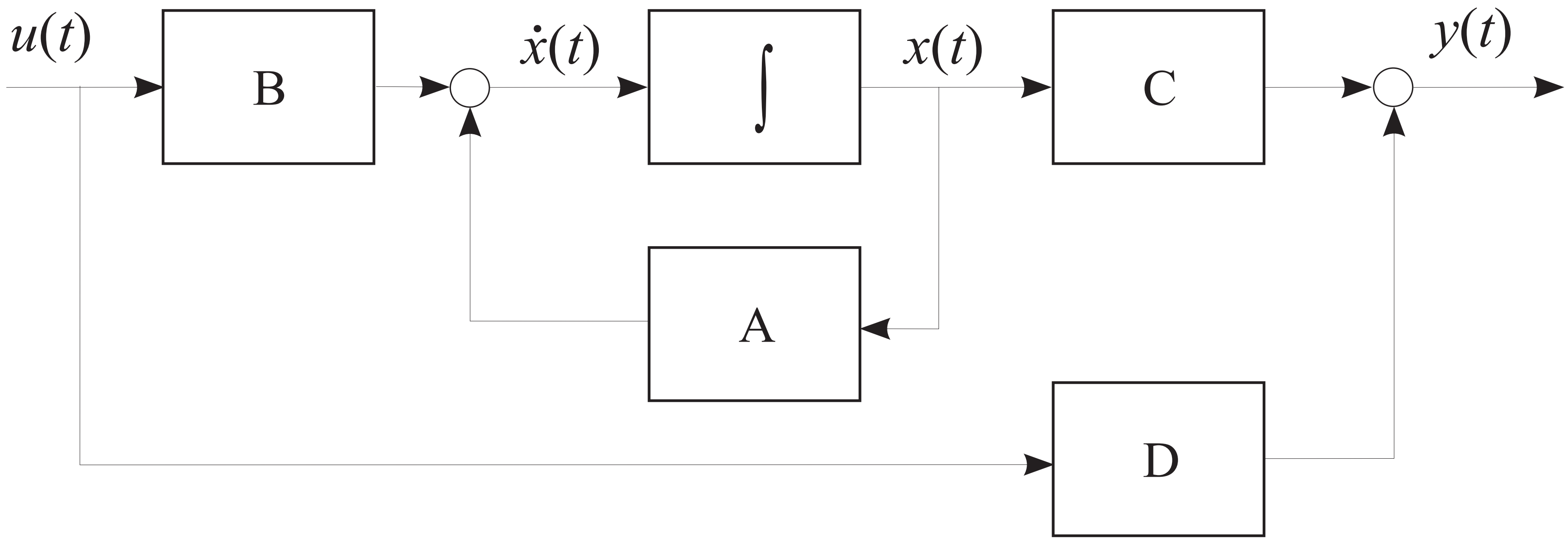
linear state-space model:

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t)\\ y(t) &= Cx(t) + Du(t)\end{aligned}$$

Continuous-Time State-Space Model

$$
\begin{aligned}
\dot{x}(t) &= Ax(t) + Bu(t) \\
y(t) &= Cx(t) + Du(t)
\end{aligned}
$$



Discrete-Time State-Space Model

$$
\begin{aligned}
x(k+1) &= \Phi x(k) + \Gamma u(k) \\
y(k) &= C x(k) + D u(k)
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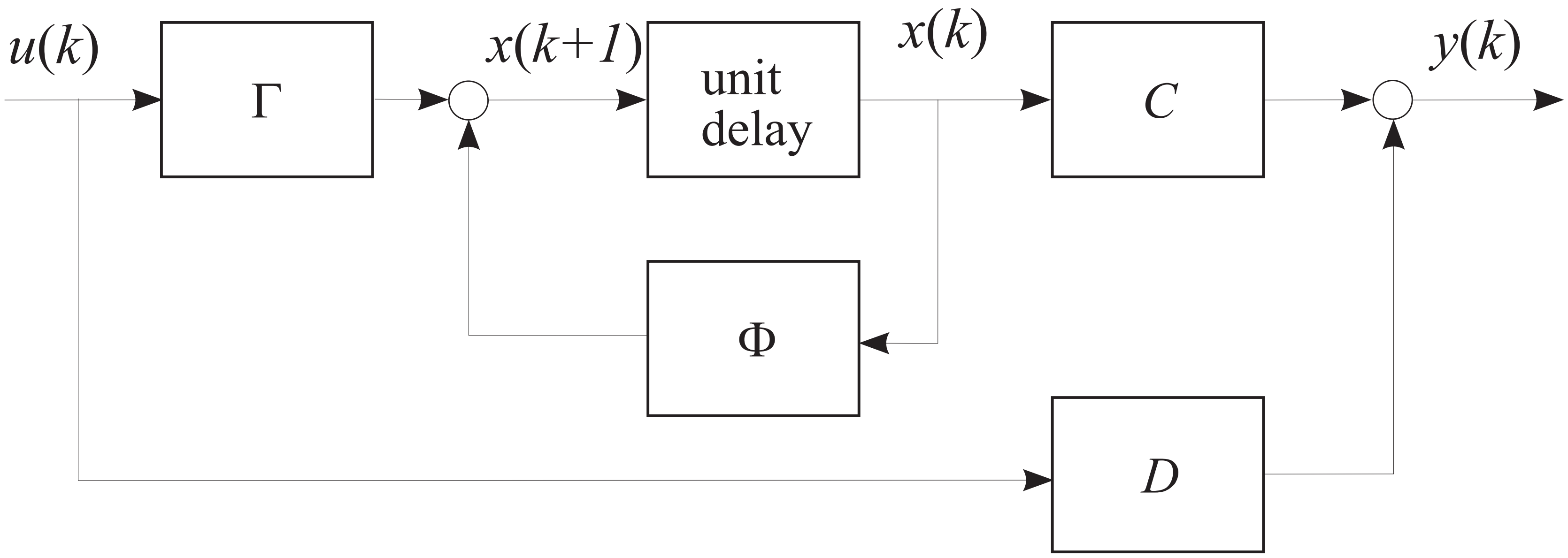


Input–Output Models

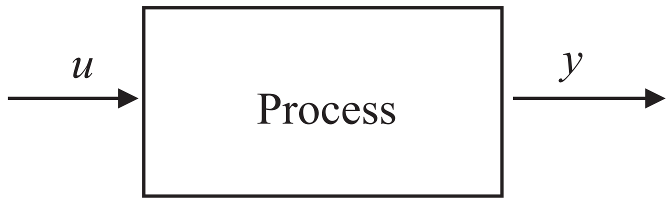
Continuous time:

$$y^{(n)}(t) = f\left(y^{(n-1)}(t), \ldots, y^{(1)}(t), y(t), u^{(n-1)}(t), \ldots, u^{(1)}(t), u(t)\right)$$

Discrete time:

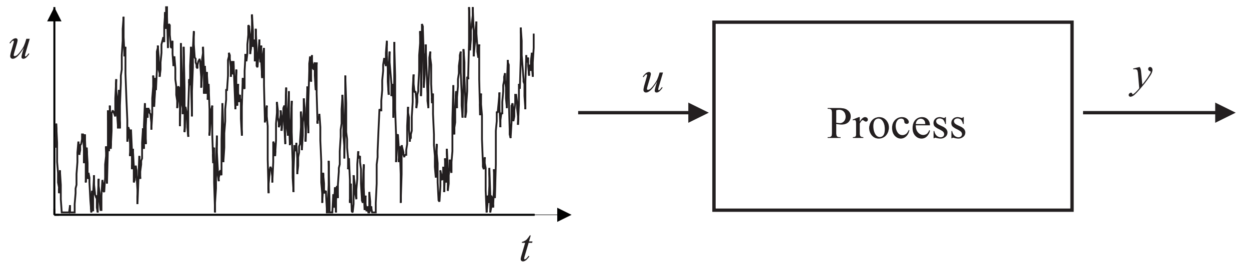
$$\begin{aligned} y(k+1) \;=\; & f(y(k), y(k-1), \ldots, y(k-n_y+1), \ldots, \\ & u(k), u(k-1), \ldots, u(k-n_u+1)) \end{aligned}$$

System Identification

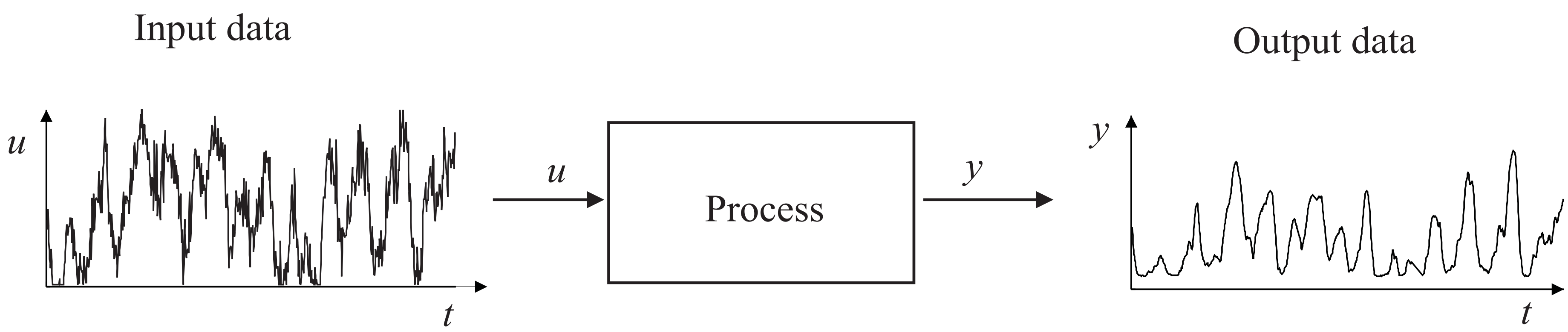


System Identification

Input data



System Identification



$$u(1), u(2), \ldots, u(N) \qquad\qquad y(1), y(2), \ldots, y(N)$$

System Identification

Given data set $\{(u(k), y(k)) \mid k = 1, 2, \ldots, N\}$**:**

1. Postulate model structure, e.g.:

$$\hat{y}(k+1) = ay(k) + bu(k)$$

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1. Postulate model structure, e.g.:

$$\hat{y}(k+1) = ay(k) + bu(k)$$

2. Form regression equations:

$$\begin{aligned} y(2) &= ay(1) + bu(1) \\ y(3) &= ay(2) + bu(2) \\ &\vdots \\ y(N) &= ay(N-1) + bu(N-1) \end{aligned}$$

in a matrix form: $\mathbf{y} = \boldsymbol{\varphi}[a \ \ b]^T$

System Identification

3. Solve the equations for $[a\ b]$ (least-squares solution):

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\mathbf{y} &= \boldsymbol{\varphi}[a\ b]^T \\
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[a\ b]^T &= [\boldsymbol{\varphi}^T\boldsymbol{\varphi}]^{-1}\boldsymbol{\varphi}^T\mathbf{y}
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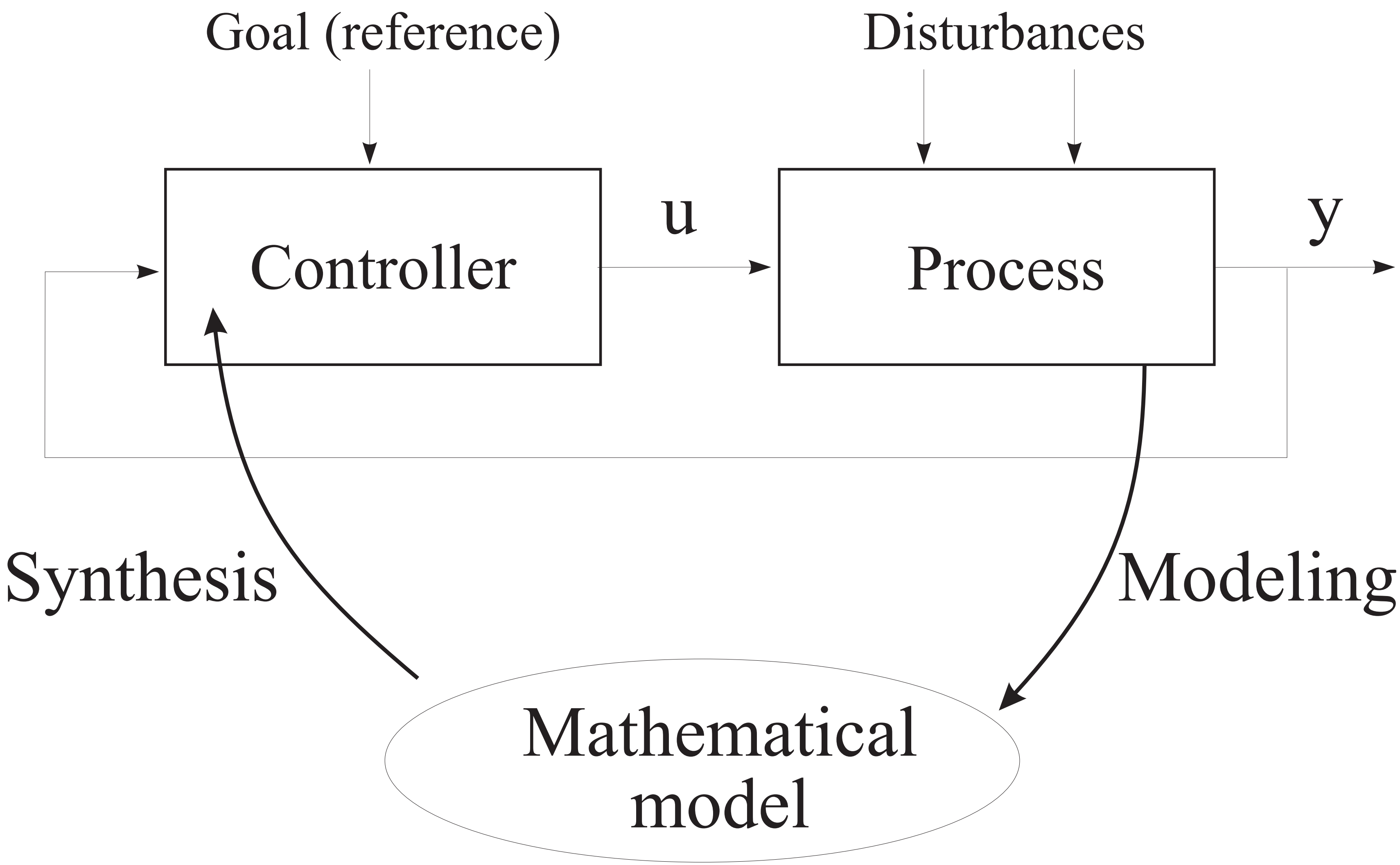
$$[a\ b]^T = [\boldsymbol{\varphi}^T\boldsymbol{\varphi}]^{-1}\boldsymbol{\varphi}^T\mathbf{y}$$

Numerically better methods are available (in MATLAB `[a b] =` φ `\ y`).

Classical Control Design



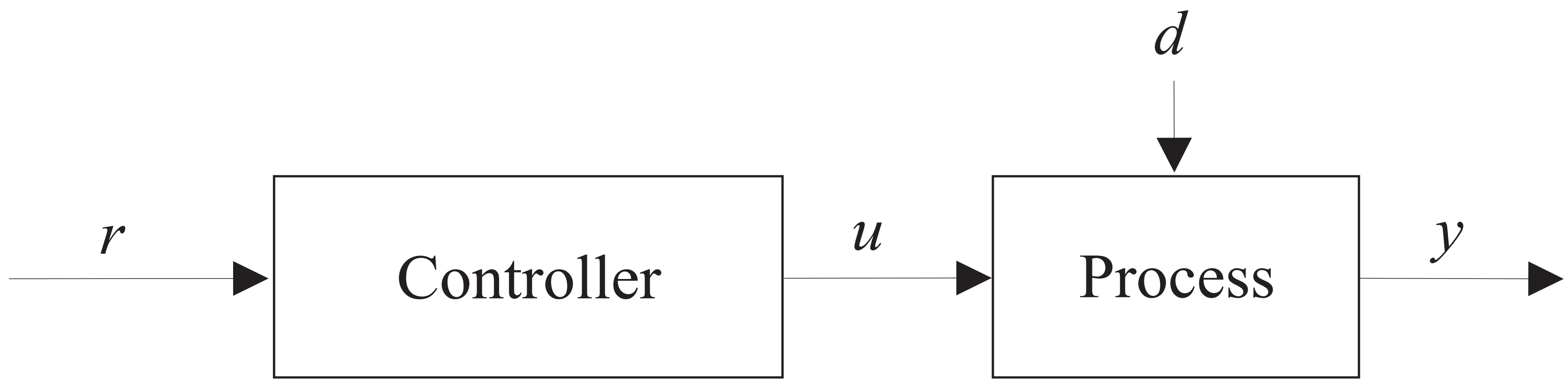
Design Procedure

- **Criterion** (goal)
  - stabilize an unstable process
  - suppress influence of disturbances
  - improve performance (e.g., speed of response)
- **Structure** of the controller
- **Parameters** of the controller (tuning)

Taxonomy of Controllers

- Presence of feedback: feedforward, feedback, 2-DOF
- Type of feedback: output, state
- Presence of dynamics: static, dynamic
- Dependence on time: fixed, adaptive
- Use of models: model-free, model-based

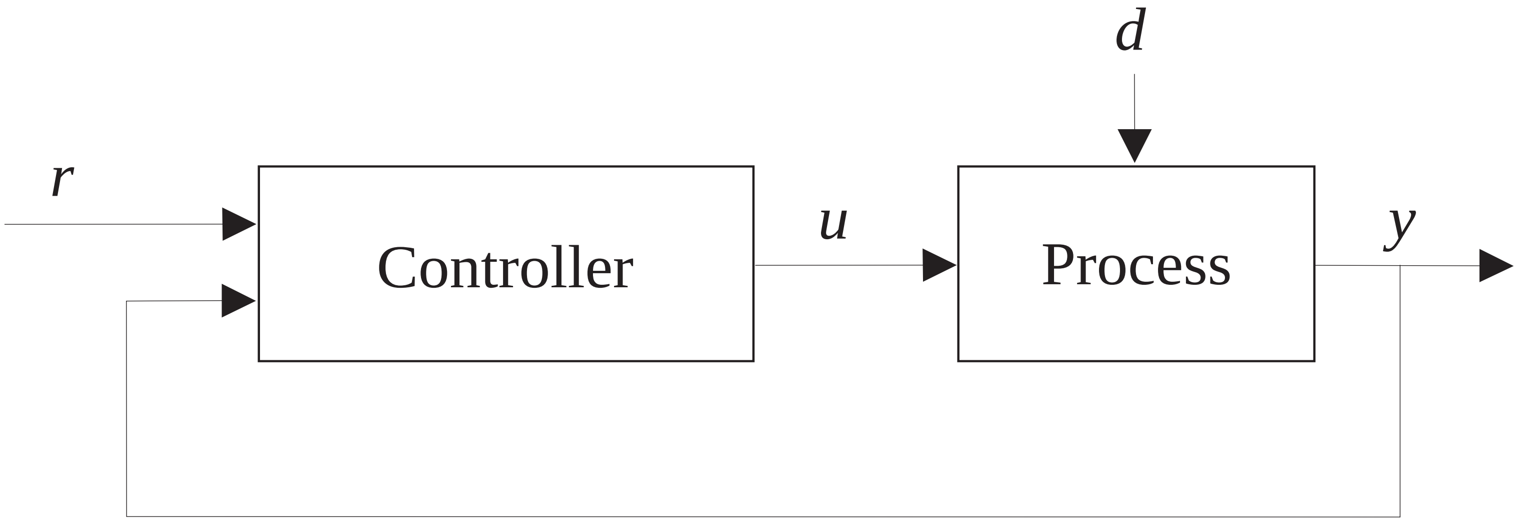
Feedforward Control



Controller:

- (dynamic) inverse of process model
- cannot stabilize unstable processes
- cannot suppress the effect of d
- sensitive to uncertainty in the model

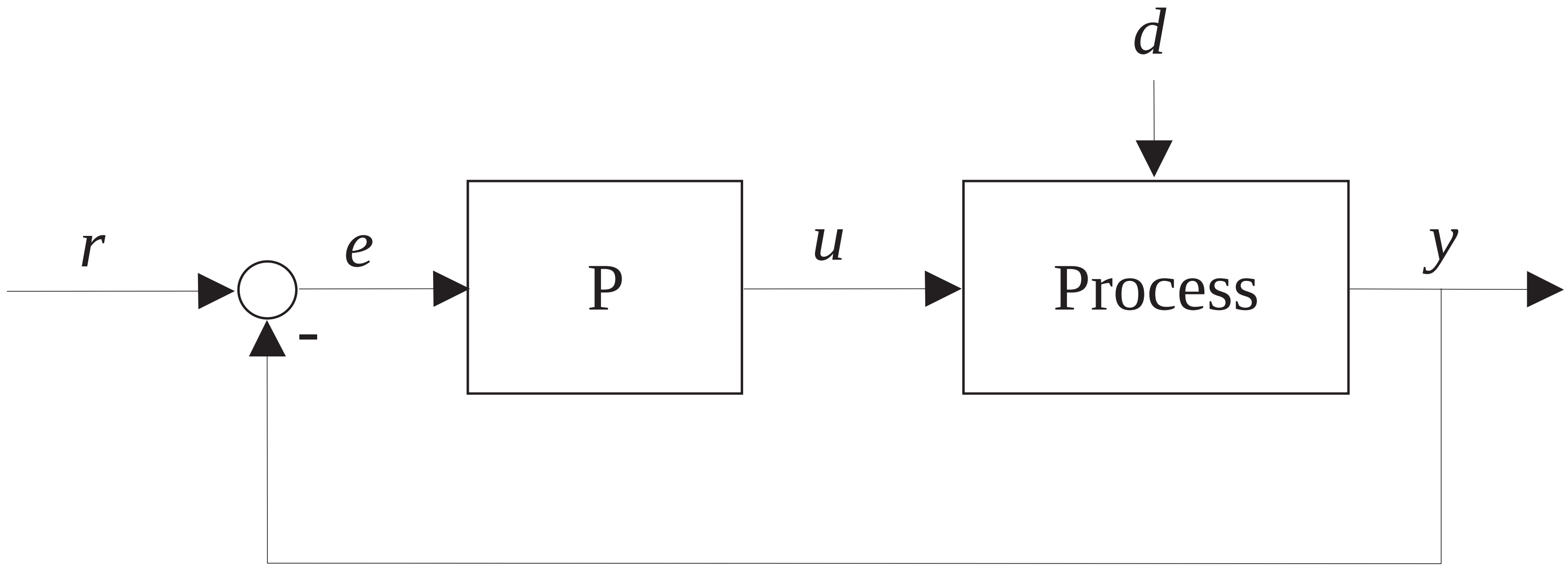
Feedback Control



Controller:

- dynamic or static ($\neq$ inverse of process)
- can stabilize unstable processes (destabilize stable ones!)
- can suppress the effect of d

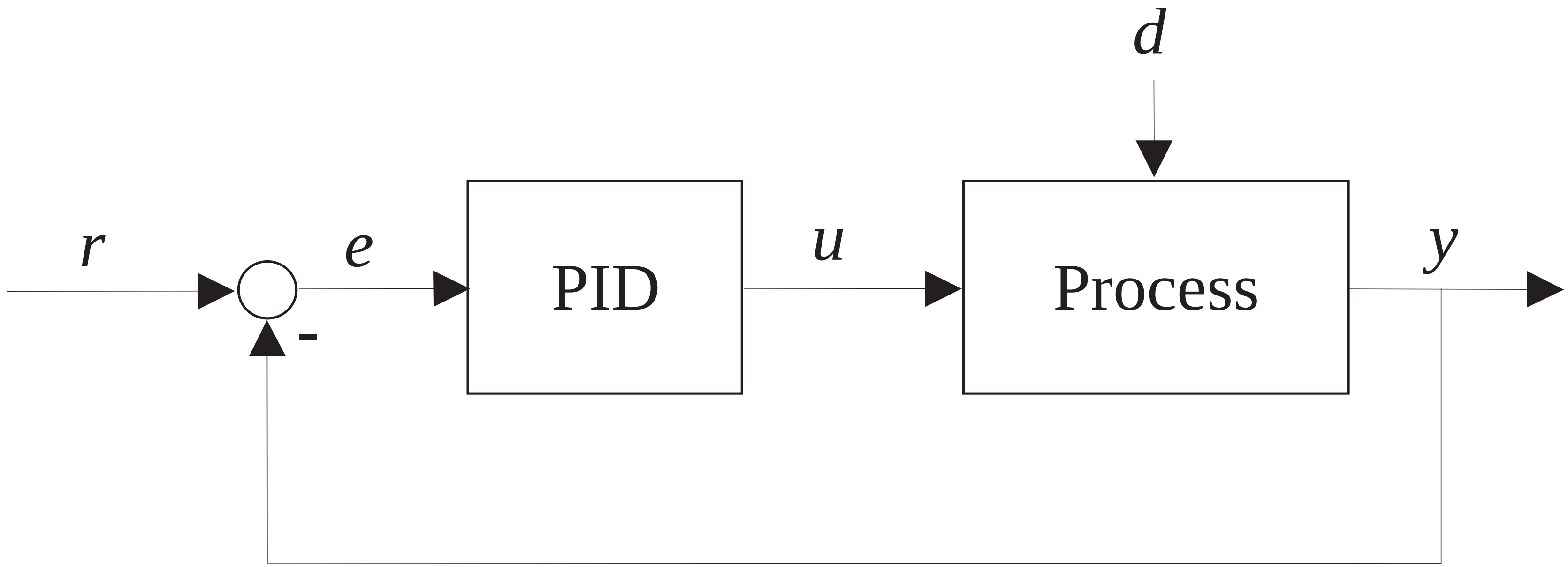
Proportional Control



Controller:

- **static gain** P**:** $u(t) = Pe(t)$

PID Control

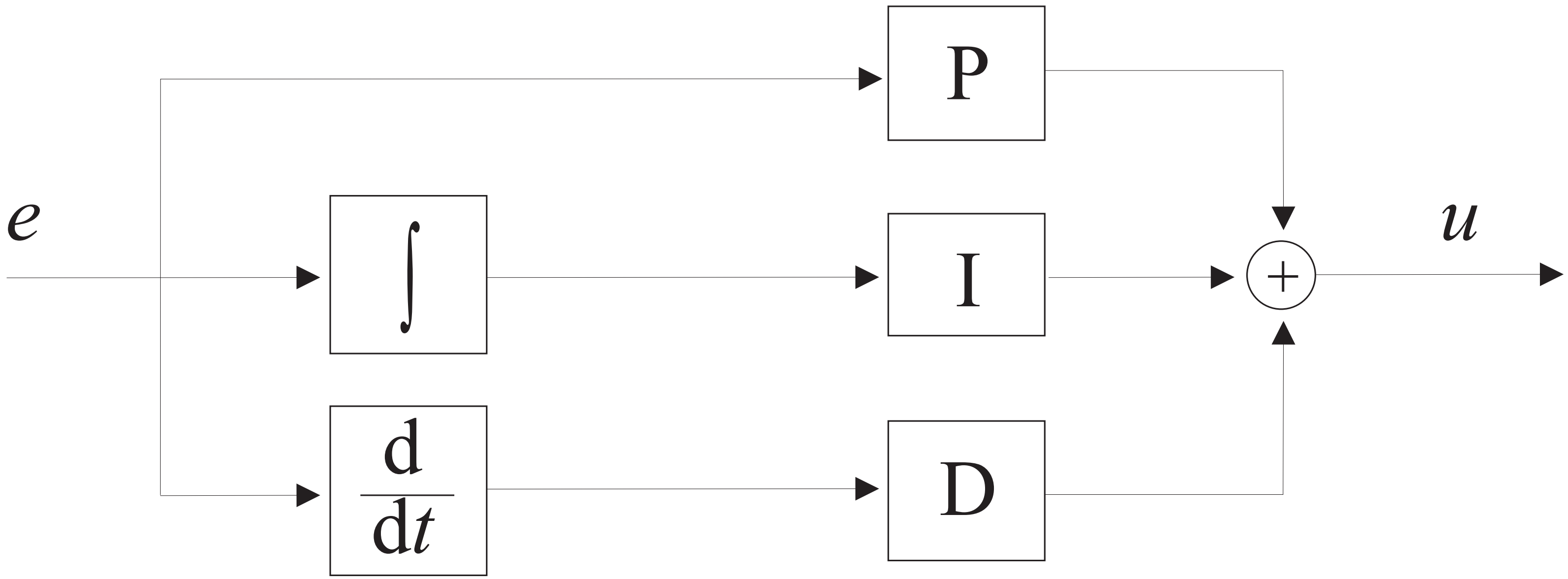


Controller:

- **dynamic:** $u(t) = Pe(t) + I \int_0^t e(\tau)d\tau + D\frac{de(t)}{dt}$
- P, I **and** D **are the proportional, integral and derivative gains, respectively**

PID Control: Internal View

$$u(t) = Pe(t) + I\int_0^t e(\tau)d\tau + D\frac{de(t)}{dt}$$



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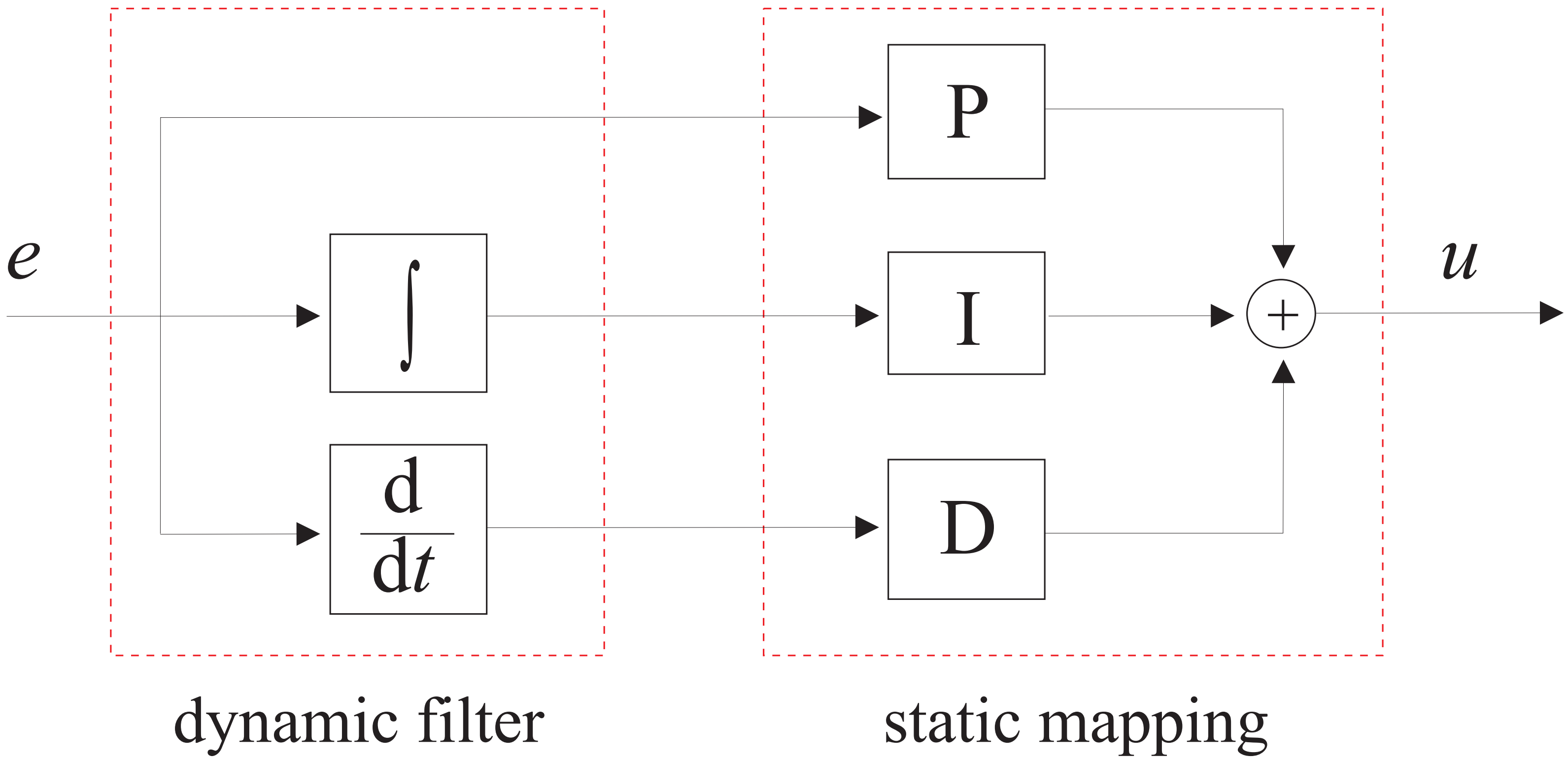
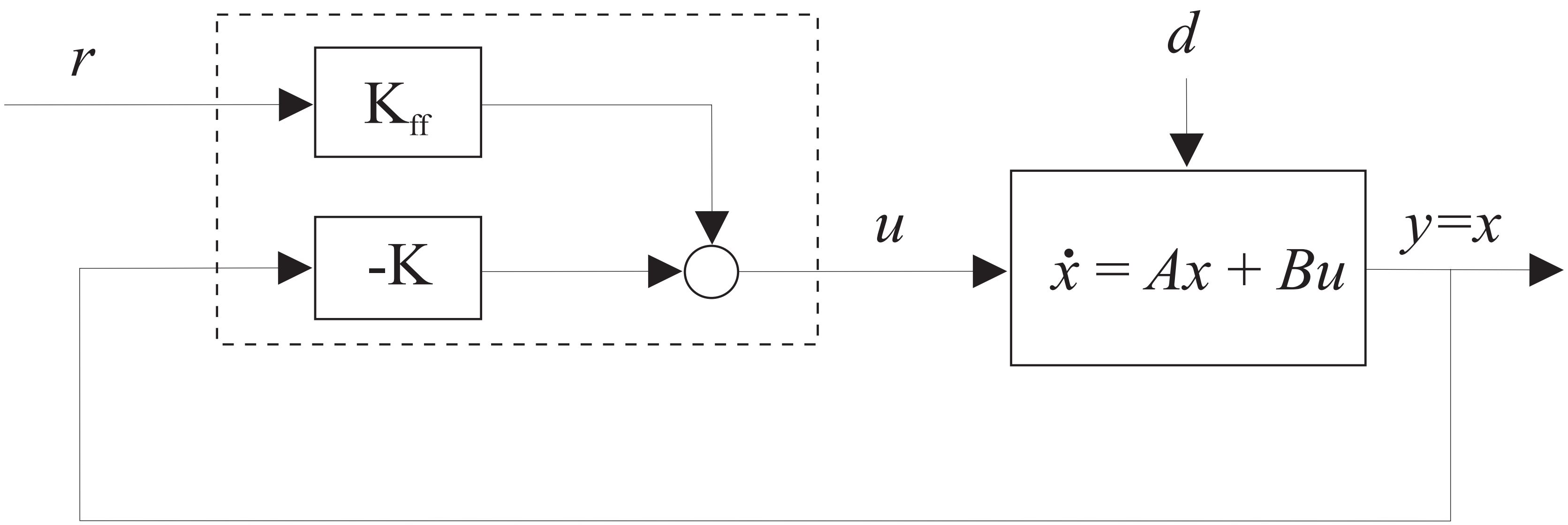


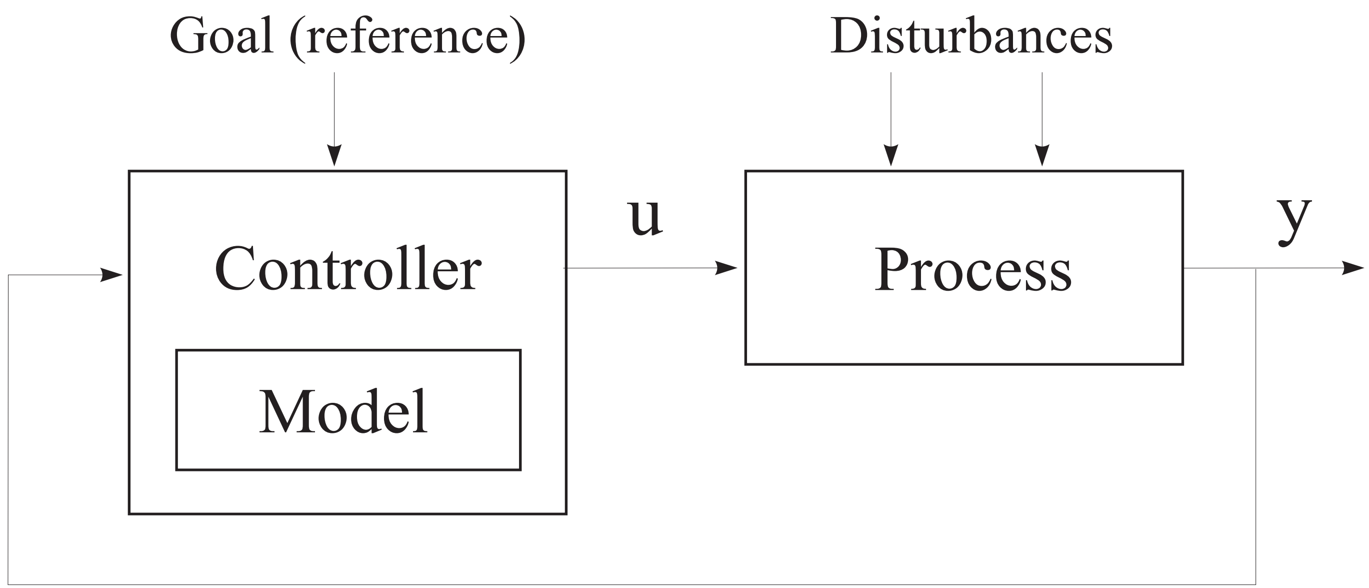
State Feedback



Controller:

- **static:** $u(t) = Kx(t)$
- K **can be computed such that** $(A + BK)$ **is stable**
- K_{ff} **takes care of the (unity) gain from** r **to** y

Model-Based Control



- state observer
- model-based predictive control
- adaptive control

Motivation for Intelligent Control

Pro's and Con's of Conventional Control

+ systematic approach, mathematically elegant

+ theoretical guarantees of stability and robustness

– time-consuming, conceptually difficult

– control engineering expertise necessary

– often insufficient for nonlinear systems

Additional Aspects

- control is a multi-disciplinary subject
- human factor may be very important
  - pilot
  - plant operator
  - user interface (e.g., consumer products)
- quest for higher machine itelligence

When Conventional Design Fails

- no model of the process available

  $\rightarrow$ mathematical synthesis and analysis impossible

  $\rightarrow$ experimental tuning may be difficult

- process (highly) nonlinear

  $\rightarrow$ linear controller cannot stabilize

  $\rightarrow$ performance limits

Example: Stability Problems

$$\frac{d^3y(t)}{dt^3} + \frac{d^2y(t)}{dt^2} + \frac{dy(t)}{dt} = y^2(t)u(t)$$

Use Simulink to simulate a proportional controller (nlpid.m)

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$$\frac{d^3y(t)}{dt^3} + \frac{d^2y(t)}{dt^2} + \frac{dy(t)}{dt} = y^2(t)u(t)$$

Use Simulink to simulate a proportional controller (nlpid.m)

Conclusions:

- **stability and performance depend on process output**
- **re-tuning the controller does not help**
- **nonlinear control is the only solution**

Intelligent Control

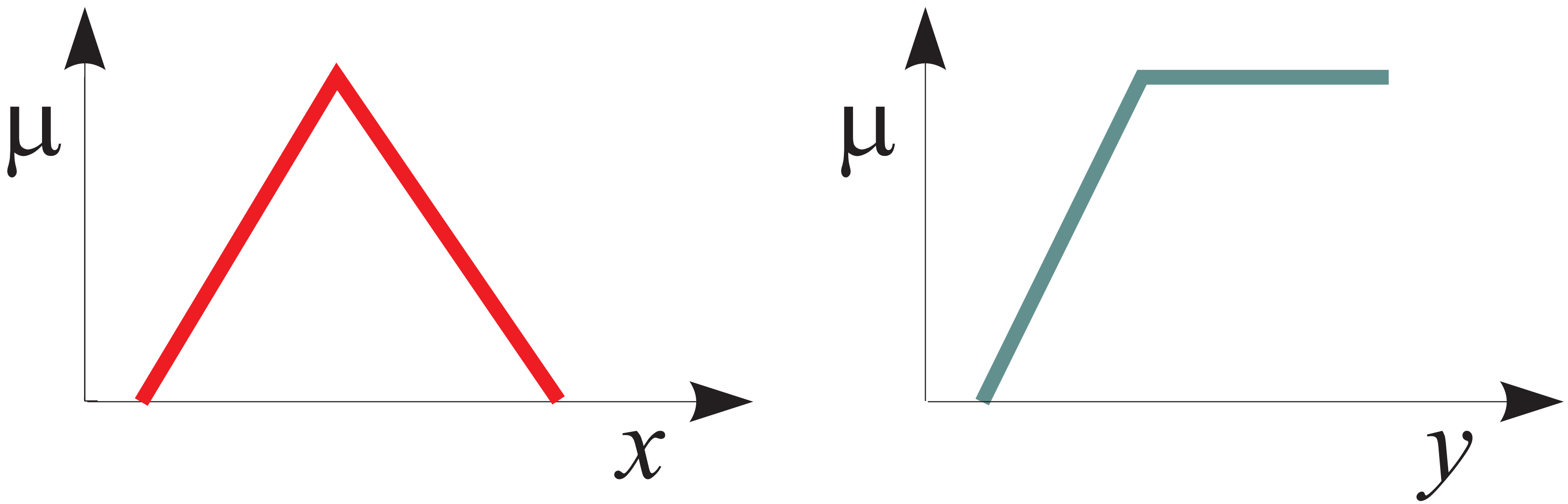
techniques motivated by human intelligence

- fuzzy systems (represent human knowledge, reasoning)
- artificial neural networks (adaptation, learning)
- genetic algorithms (optimization).

$\Rightarrow$ *computational intelligence, soft computing*

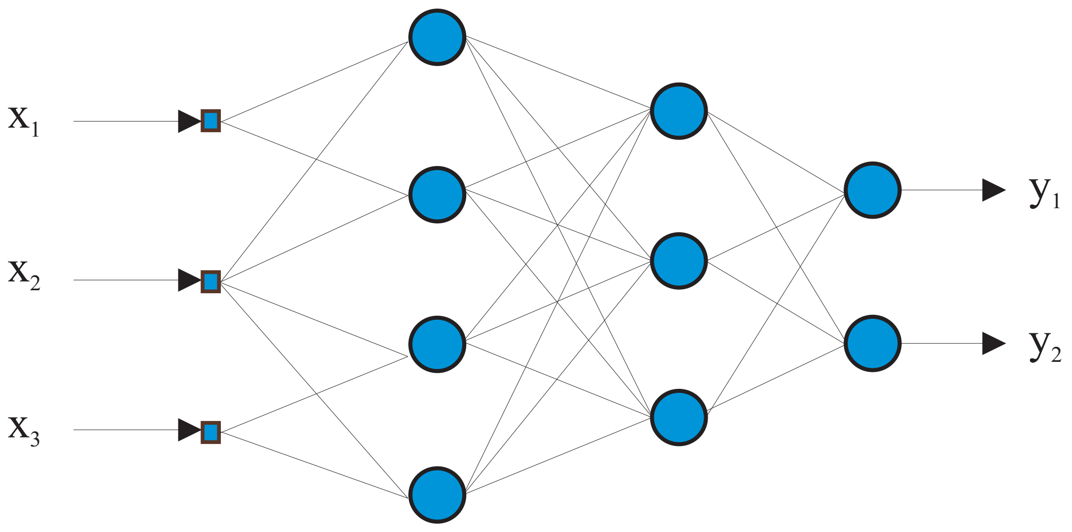
Knowledge Representation by If–Then Rules

If x is *Medium* **then** y is *Large*



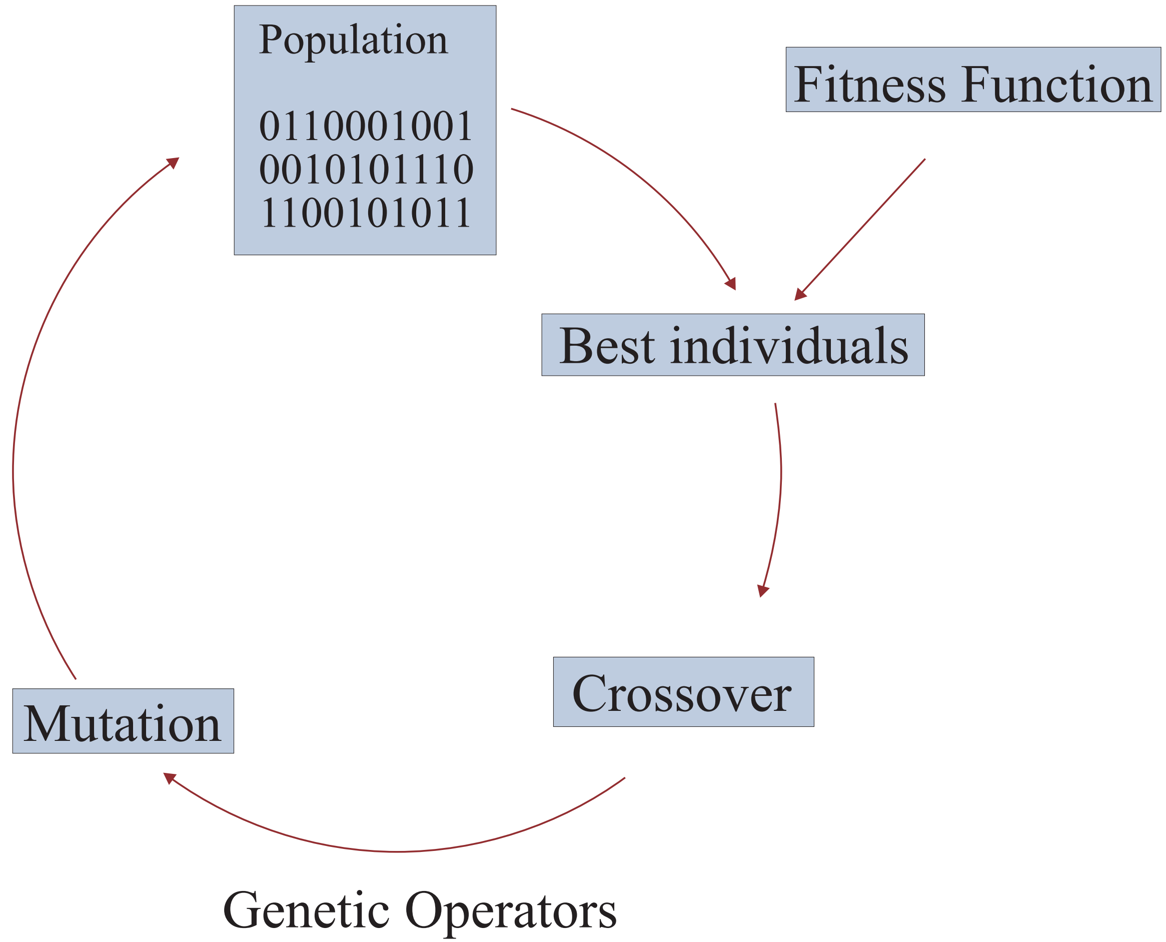
Artificial Neural Networks

Function approximation by imitating biological neural networks.



Learning, adaptation, optimization.

Genetic Algorithms

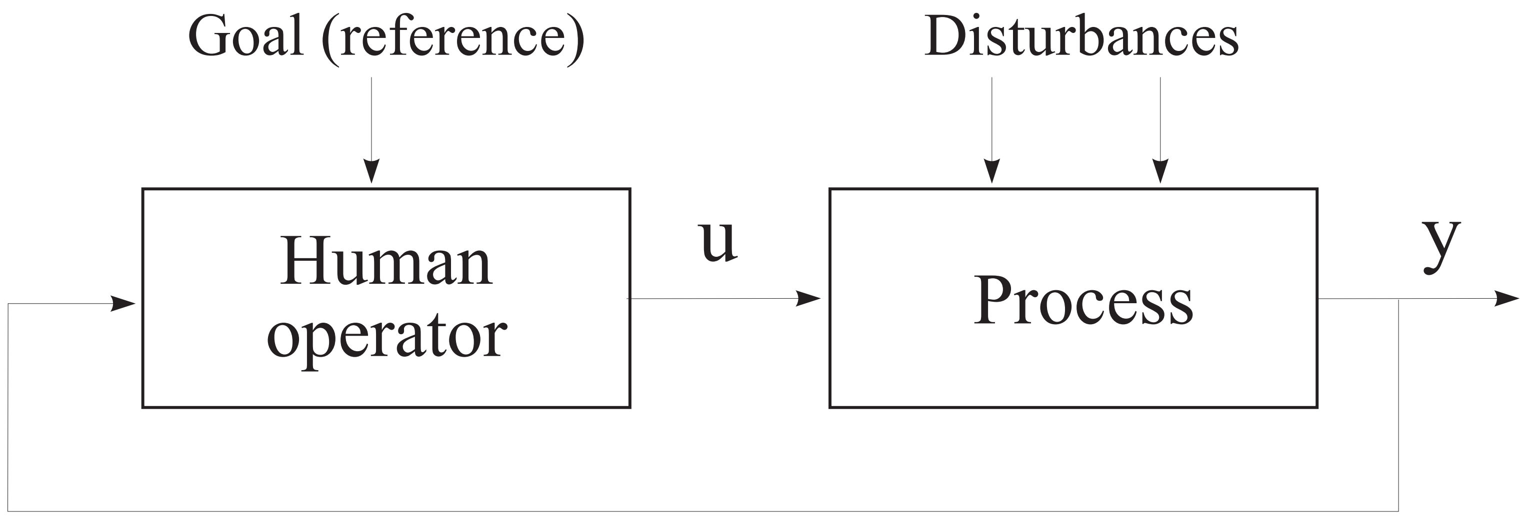


Optimization by imitating natural evolution.

Intelligent Control

- Fuzzy knowledge-based control
- Fuzzy data analysis, modeling, identification
- Learning and adaptive control (neural networks)
- Reinforcement learning

Direct Fuzzy Control



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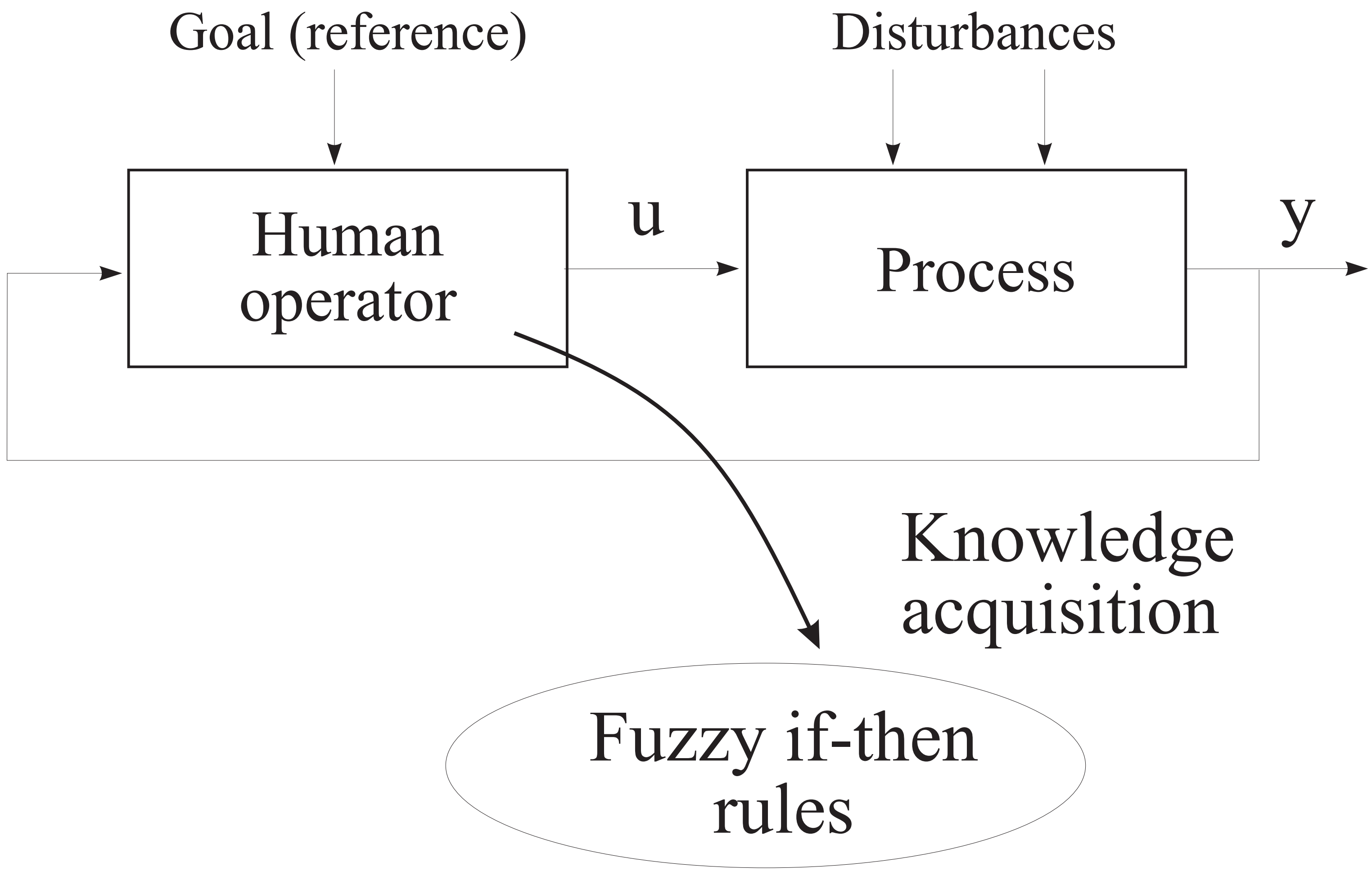

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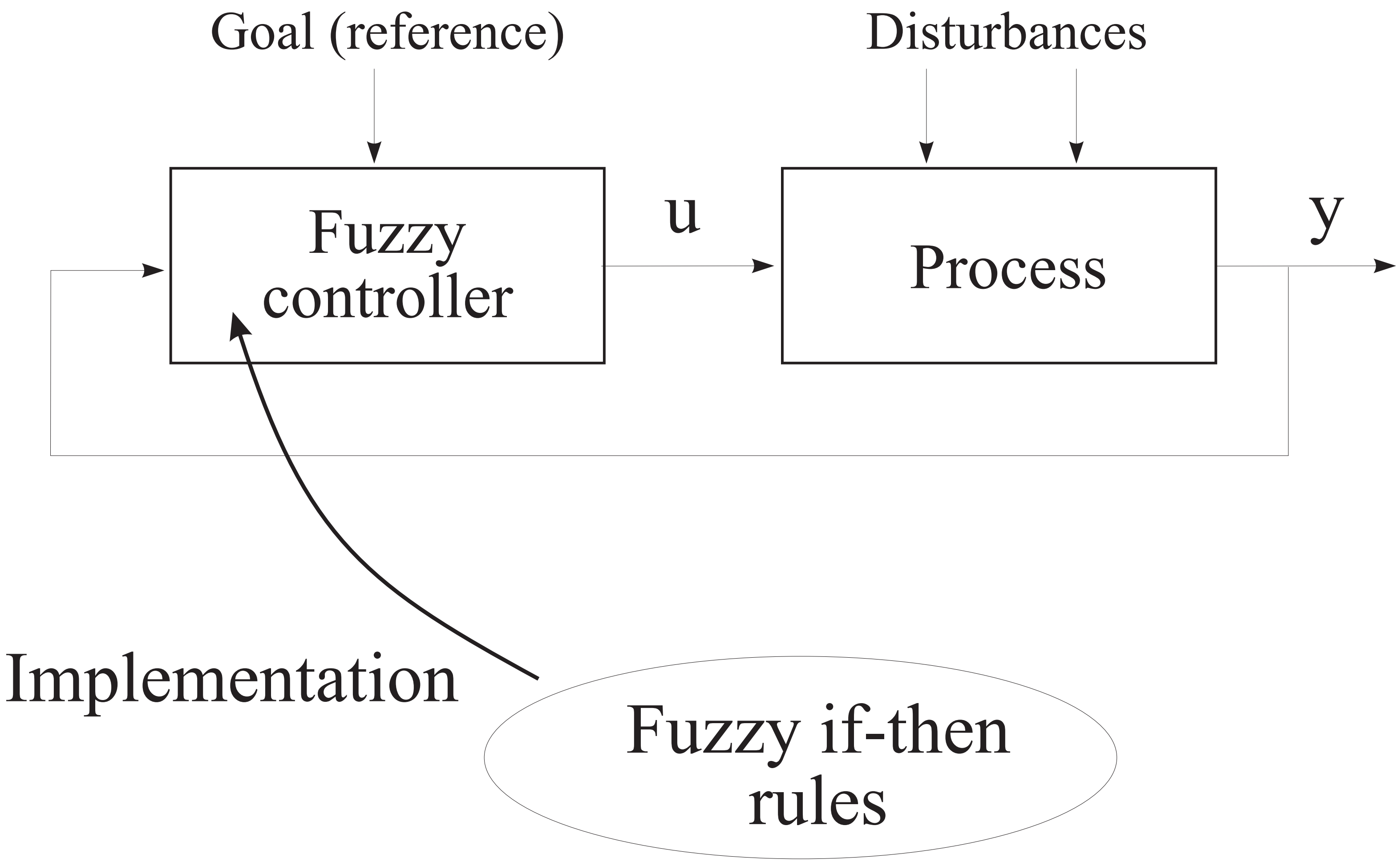

Fuzzy Sets and Fuzzy Logic

Relatively new methods for representing uncertainty and reasoning under uncertainty.

Types of uncertainty:

- chance, randomness (stochastic)
- imprecision, vagueness, ambiguity (non-stochastic)

Vagueness in If–Then Rules

If **temperature** in the burning zone ***is OK***, and

oxygen percentage in the exhaust gases ***is Low***, and

temperature at the back-end ***is High***,

then reduce fuel ***Slightly*** and reduce fan speed ***Moderately***.

Fuzzy Sets and Fuzzy Logic

Proposed in 1965 by L.A. Zadeh

(Fuzzy Sets, Information Control, vol. 8, pp. 338–353)

- generalization of ordinary set theory
- '70 first applications, fuzzy control (Mamdani)
- '80 industrial applications, train operation, pattern recognition
- '90 consumer products, cars, special HW, SW.

The term "fuzzy logic" often also denotes fuzzy sets theory and its applications (e.g., fuzzy logic control).

Applications of Fuzzy Sets