Lecture 6

Summary on System Identification

Course Outline

- Introduction and overview on system identification
- Non-recursive (off-line) identification methods
- Recursive (on-line) identification methods (III), practical aspects and applications of system identification, and summary

The System Identification Procedure

1. *Experiment design.* If possibly choose the input signal such that the data become maximally informative. Reduce the influence of noise.

2. Choose the *model structure.* Use priori knowledge and engineering intuition. Most important and most difficult step. (Do not estimate what you already know)

3. *Parameter estimation.* Determine the best model in the model structure (find optimal $\boldsymbol{\theta}$ using *e.g.*, the least squares method).

4. *Model validation.* Is the model good enough? Good is subjective, and depends on the purpose with the model.

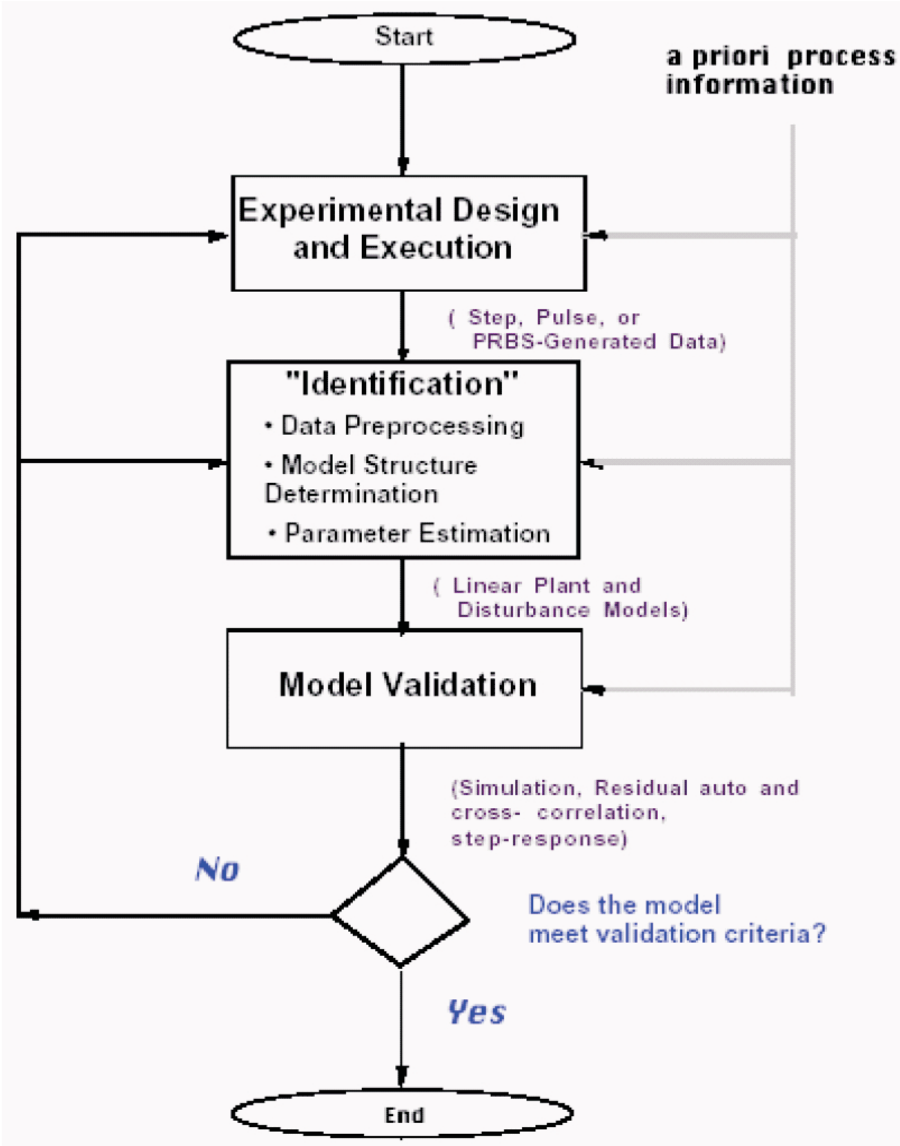

Figure 1: Procedure of System Identification

Experiment Design

- Choice of input signal.
- Choice of sampling period.
- What signals to measure, and what type of sensors to use.
- How much data is needed.
- Experimental conditions.
  - Feedback in the data?
  - Test for linearity.
  - Test for time-invariance.

Choice of Input Signal

- Signal amplitude
  - Sufficiently small to ensure that we remain in the linear region of the system.
  - Sufficiently large to ensure that we have good excitation.
- Spectral range. The input should have most of its energy in the interesting frequency regions (depends on the application).
- *Persistently exciting* of a sufficient order! $\Rightarrow$ Required to assure consistency of parametric models.
- Physical limitations.

Persistent Excitation

Define:

$$C_n = \lim_{t\to\infty} \frac{1}{t}\Phi^T\Phi = \begin{bmatrix} c(0) & c(1) & \cdots & c(n-1) \\ c(1) & c(0) & \cdots & c(n-2) \\ \vdots & \vdots & \ddots & \vdots \\ c(n-1) & c(n-2) & \cdots & c(0) \end{bmatrix}$$

where $c(k)$ are the empirical covariances of the input. That is:

$$c(k) = \lim_{t\to\infty} \frac{1}{t}\sum_{j=1}^{t} u(j)u(j-k)$$

Definition: A signal u is called *persistently exciting* (PE) of order n if the matrix C_n is positive definite.

Examples:

- **White noise**: $u(t)$ is white noise, with zero mean and variance σ^2. Then $c(n) = \sigma^2 \delta_n$, and $C_n = \sigma^2 I_n$, which is always positive definite. Thus C_n is nonsingular for all n, and white noise signal is PE of all orders.

- **Step signal**: $u(t)$ is a step of magnitude σ, then $c(k) = \sigma^2$, and C_n is nonsingular only if $n = 1$. Then a step is PE of order 1.

- **Impulse signal**: $u(t) = 1$ for $t = 0$, and 0 otherwise. This gives $c(n) = 0$ for all n and $C_n = 0$. Therefore, this signal is not PE of any order.

Important Note: It is necessary for consistent estimation of an n-th order system that the input signal be at least persistently exciting of order $2n = n + m$, assuming $n = m$.

Determination of Model Structure

- Linear versus nonlinear, static versus dynamic, ...
- Algorithm complexity
- Computational time and power
- Depends on the application. Simple or more sophisticated model.

Static Models

Typical examples:

- Trends and non-zero means
- Cyclic components and harmonics

Model:

$$y(t) = \boldsymbol{\varphi}^T(t)\boldsymbol{\theta}$$

where $\boldsymbol{\varphi}(t)$ is deterministic (does not depend on old values of $y(t)$).

Example: $y(t) = \boldsymbol{\varphi}^T(t)\boldsymbol{\theta}$, $\boldsymbol{\varphi}^T(t) = [1\ t\ t^2]$.

Dynamic Models

General model:

$$y(t) = G(q^{-1})u(t) + H(q^{-1})e(t)$$

$$y(t) = \boldsymbol{\varphi}^T(t)\boldsymbol{\theta} + v(t)$$

where $\boldsymbol{\varphi}(t)$ depends on old values of $y(t)$.

- Typical models:
  ARX: $A(q^{-1})y(t) = B(q^{-1})u(t) + \varepsilon(t)$
  ARMAX: $A(q^{-1})y(t) = B(q^{-1})u(t) + C(q^{-1})\varepsilon(t)$
  OE: $y(t) = \frac{B(q^{-1})}{F(q^{-1})}u(t) + \varepsilon(t)$
  FIR: $y(t) = B(q^{-1})u(t) + \varepsilon(t)$
- The models have a certain dynamic range and are valid around a particular “working point”.

Identification Method

- Nonparametric Methods
  - Transient response, frequency response, spectral analysis
  - Gives basic information about the system, with unsatisfactory accuracy, and is useful for validation
- Parametric Methods: Static and dynamic cases
  - Least squares methods, instrumental variable methods, prediction error methods
  - Good accuracy. Easy to use for *e.g.*, control
- On-line or Off-line Methods

Least Squares Methods - off-line methods

System:

$$y(t) = \boldsymbol{\varphi}^T(t)\boldsymbol{\theta} + v(t), \quad t = 1, \ldots, N$$

$$\Rightarrow \qquad \boldsymbol{Y} = \boldsymbol{\Phi}\boldsymbol{\theta} + \boldsymbol{v}$$

where $v(t)$ is a disturbance and $E\boldsymbol{v} = 0$, $E\boldsymbol{v}\boldsymbol{v}^T = \boldsymbol{R}$.

Estimate:

$$\hat{\boldsymbol{\theta}} = (\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}\boldsymbol{\Phi}^T\boldsymbol{Y} = \Big[\sum_{t=1}^{N} \boldsymbol{\varphi}(t)\boldsymbol{\varphi}^T(t)\Big]^{-1}\Big[\sum_{t=1}^{N} \boldsymbol{\varphi}(t)y(t)\Big]$$

Further Details on Least Squares Methods

For a given dynamic system

$$A(q^{-1}, \boldsymbol{\theta})y(t) = B(q^{-1}, \boldsymbol{\theta})u(t) + e(t)$$

$$\Rightarrow \qquad y(t) = \boldsymbol{\varphi}^T(t)\boldsymbol{\theta} + e(t)$$

where

$$\boldsymbol{\varphi}(t) = [\,-y(t-1)\ \ldots\ -y(t-n_a)\ u(t-1)\ \ldots\ u(t-n_b)]^T$$

$$\boldsymbol{\theta} = [a_1\ \ldots\ a_{n_a}\ b_1\ \ldots\ b_{n_b}]^T$$

Problem: Find an estimate of $\boldsymbol{\theta}$ for given measurement $y(1), \boldsymbol{\varphi}(1), \ldots, y(N), \boldsymbol{\varphi}(N)$.

Solution: Introduce the *equation error*

$$\varepsilon(t) = y(t) - y_m(t) = y(t) - \boldsymbol{\varphi}^T(t)\boldsymbol{\theta}, \quad t = 1, \ldots, N$$

or compactly

$$\boldsymbol{\varepsilon} = \boldsymbol{Y} - \boldsymbol{Y}_m = \boldsymbol{Y} - \boldsymbol{\Phi}\boldsymbol{\theta}$$

Least squares method: Choose $\boldsymbol{\theta}$ such that $\varepsilon^2(t)$ is small for all t:

$$\hat{\boldsymbol{\theta}}_{LS} = \arg\min_{\boldsymbol{\theta}} V(\boldsymbol{\theta})$$

$$V(\boldsymbol{\theta}) = \frac{1}{2}\sum_{t=1}^{N} \varepsilon^2(t) = \frac{1}{2}\boldsymbol{\varepsilon}^T\boldsymbol{\varepsilon} = \frac{1}{2}(\boldsymbol{Y} - \boldsymbol{\Phi}\boldsymbol{\theta})^T(\boldsymbol{Y} - \boldsymbol{\Phi}\boldsymbol{\theta})$$

Results: Assume that $\boldsymbol{\Phi}^T\boldsymbol{\Phi}$ is invertible. Then the solution of the above optimization is given by solving $\frac{\partial}{\partial\boldsymbol{\theta}}V(\boldsymbol{\theta}) = 0$, which leads to

$$\hat{\boldsymbol{\theta}}_{LS} = \left(\boldsymbol{\Phi}^T\boldsymbol{\Phi}\right)^{-1}\boldsymbol{\Phi}^T\boldsymbol{Y} = \Big[\sum_{t=1}^{N}\boldsymbol{\varphi}(t)\boldsymbol{\varphi}^T(t)\Big]^{-1}\Big[\sum_{t=1}^{N}\boldsymbol{\varphi}(t)y(t)\Big]$$

Note: The above LS algorithm is also referred as to Block/Batch LS.

Static case: Here $\boldsymbol{\varphi}(t)$ is deterministic.

- Generally consistent estimates
- For *finite* value of N we have:

$$E\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}_0$$
$$\operatorname{cov}\hat{\boldsymbol{\theta}} = (\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}\boldsymbol{\Phi}^T\boldsymbol{R}\boldsymbol{\Phi}(\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1}$$

- Can be extended to include the weighted least squares and the BLUE.

Dynamic case: $\boldsymbol{\varphi}(t)$ depends on old values of $y(t)$.

- Consistent estimates if $v(t) = e(t)$ is white noise! $(Ee^2(t) = \lambda^2)$
- Asymptotically $(N \to \infty)$ it holds $(v(t) = e(t))$

$$\operatorname{cov}\hat{\boldsymbol{\theta}} = \lambda^2\left[E\boldsymbol{\varphi}(t)\boldsymbol{\varphi}^T(t)\right]^{-1}$$

On-line Identification Methods

- In many cases an on-line estimate is required. e.g. adaptive signal processing, tracking time-varying parameters, fault diagnosis, etc.
- Most off-line methods can be converted into on-line methods (exactly or approximately).

On-line methods covered:

- Recursive Least Squares (RLS) Methods

RLS

Algorithm:

At time $t = 0$: Choose initial values of $\hat{\boldsymbol{\theta}}(0)$ and $\boldsymbol{P}(0)$

At each sampling instant, update $\boldsymbol{\varphi}(t)$ and compute

$$\hat{\boldsymbol{\theta}}(t) = \hat{\boldsymbol{\theta}}(t-1) + \boldsymbol{K}(t)\varepsilon(t)$$

$$\varepsilon(t) = y(t) - \boldsymbol{\varphi}^T(t)\hat{\boldsymbol{\theta}}(t-1)$$

$$\boldsymbol{K}(t) = \boldsymbol{P}(t)\boldsymbol{\varphi}(t)$$

$$\boldsymbol{P}(t) = \left[\boldsymbol{P}(t-1) - \frac{\boldsymbol{P}(t-1)\boldsymbol{\varphi}(t)\boldsymbol{\varphi}^T(t)\boldsymbol{P}(t-1)}{1 + \boldsymbol{\varphi}^T(t)\boldsymbol{P}(t-1)\boldsymbol{\varphi}(t)}\right]$$

Question: How to obtain/derive this recursive version of LS from the block/batch LS?

Weighted RLS

Algorithm:

At time $t = 0$: Choose initial values of $\hat{\boldsymbol{\theta}}(0)$ and $\boldsymbol{P}(0)$

At each sampling instant, update $\boldsymbol{\varphi}(t)$ and compute

$$\hat{\boldsymbol{\theta}}(t) = \hat{\boldsymbol{\theta}}(t-1) + \boldsymbol{K}(t)\varepsilon(t)$$

$$\varepsilon(t) = y(t) - \boldsymbol{\varphi}^T(t)\hat{\boldsymbol{\theta}}(t-1)$$

$$\boldsymbol{K}(t) = \boldsymbol{P}(t)\boldsymbol{\varphi}(t)$$

$$\boldsymbol{P}(t) = \frac{1}{\lambda(t)}\left[\boldsymbol{P}(t-1) - \frac{\boldsymbol{P}(t-1)\boldsymbol{\varphi}(t)\boldsymbol{\varphi}^T(t)\boldsymbol{P}(t-1)}{\lambda(t) + \boldsymbol{\varphi}^T(t)\boldsymbol{P}(t-1)\boldsymbol{\varphi}(t)}\right]$$

Model Validation

A model is of no use unless it is validated!

– Compare model simulation/prediction with real data in time domain

– Compare estimated models frequency response and spectral analysis result in frequency domain

– Perform statistical tests on prediction errors

Conclusions

- System identification is a powerful technique to model dynamic systems.
- Applications in virtually all disciplines of science.
- Implemented in *e.g.*, MATLAB.
- Where to learn more: Nice textbook by Ljung, journals (Automatica) and conferences (IFAC SYSID).