16. Some practical aspects

- Design of the experimental condition
- Treating nonzero means and drifts in disturbances
- Time delays
- Initial conditions
- Choice of identification methods
- Local minima
- Model verification

System identification procedures

1. *Looking at the data:* nonlinear effects, portions of the data that carry information, detrend the mean

2. *Getting a feel for the difficulties:* use spectral analysis and correlation analysis and compare the results with the response from the ARX models

3. *Examining the difficulties:* model unstable, feedback in data, noise model, model order, additional inputs, nonlinear effects

4. *Fine tuning orders and noise structures:* compare different models by considering

   - Fit between simulated and measured output
   - Residual analysis test
   - Pole zero cancellations

Design of the experimental condition

1. *Choice of input signal*
   - identifying an nth-order model typically requires $u(t)$ is persistently exciting of order $2n$
   - choice of amplitude
     - avoid large amplitude to prevent large fluctations or operating in nonlinear region
     - use large amplitude to increase signal-to-noise ratio
   - contain most of its energy in the interesting frequency regions

2. *Choice of sampling interval*
   - high sampling rate: the disturbances may have large influence
   - low sampling rate: the data may contain little information about the high frequency
   - high-frequency noise should be filtered out to decrease aliasing effect and increase signal-to-noise ratio

Treating nonzero means

- Using data with non-zero mean could lead to biased estiamtes
- Two approaches for treating nonzero means
  1. Estimate the mean values explicitly
     - Fit a polynomial trend $y_r(t) = a_0 + a_1 t + \ldots + a_r t^r$ to the output using linear regression and compute the detrended data:

$$\tilde{y}(t) = y(t) - y_r(t)$$

     - Estimate the means during the parameter estimation phase

$$y(t) = G(q^{-1};\theta)u(t) + H(q^{-1};\theta)\nu(t) + m(\theta)$$

  2. Use models for th differenced data

$$\Delta y(t) = y(t) - y(t-1)$$

Time delays

- The general model structure

$$y(t) = G(q^{-1};\theta)u(t) + H(q^{-1};\theta)\nu(t)$$

can in fact, cover cases with a time delay since

$$G(q^{-1};\theta) = \sum_{i=1}^{\infty} g_i(\theta)q^{-1}$$

If there is a delay of k sampling intervals, then it is required that

$$g_i(\theta) = 0, \quad i = 1, 2, \ldots, k-1$$

- Time delays for ARMAX models

$$A(q^{-1})y(t) = q^{-(k-1)}B(q^{-1})u(t) + C(q^{-1})\nu(t)$$

- Compute the delayed input

$$\tilde{u}(t) = q^{-(k-1)}u(t) = u(t-k+1), \quad t = k, k+1, \ldots, N$$

- Estimate the parameters of the ARMAX model (applying a standard method that works with unit time delay) using $\tilde{u}(t)$ instead of $u(t)$
- Alternatively, one can shift the output sequence

$$\tilde{y}(t) = y(t+k-1), \quad t = 1, 2, \ldots, N-k+1$$

  and use $\tilde{y}(t)$ for estimating the ARMAX model instead of $y(t)$

- The determination of time delay (k) can be made using the same methods as those for determination of the model order

- However, one should use these methods with care if the time delay and the model order are determined simultaneously

Initial conditions

- If a priori information is available, then appropriate values can be used
- Otherwise, set the initial values to zero
- Include the unknown intial values in the parameter vector ($e.g.$, find the exact ML estimates)
- Note that the initial conditions cannot be consistently estimated using a PEM or another estimation method

Choice of the identification method

The methods are ordered in terms of improved accuracy and increased computational complexity

- Transient analysis
- Frequency analysis
- The least squares method
- The instrumental variable method
- The prediction error method

When choosing the identification method, one should keep in mind that

- it is trade-off between the accuracy and computational effort
- the methods are tied to certain types of model structure

Local minima

- For PEM, there is a potential risk that the algorithm is stuck at a local minimum
- When the number of data (N) is large and assume that the true system is included in the model structure, then the global minimum can be guaranteed for certain classes of models such as
  - scalar ARMA
  - multivariable MA
  - SISO output error model
- The nonglobal minimum could lead to a bad model which provides a poor description of the data
- One normally should try a larger model structure
- If it is believed that the algorithm is stuck at a local minimum, one can try to use another starting point

Model verification

Using the model in practice and check if it is likely to describe the system adequately

- *Test of linearity:* Repeat the experiment with another amplitude of the input
- *Test of time invariance:* Use data from two different experiments where the parameter estimates are determined from the first data set, and the model output is computed fro the second set of data
- *Test for existence of feedback:* If $u(t)$ is determined by feedback from $y(t)$, then the input $u(t)$ should be dependent on past residuals but independent of future values of the residuals

$$R_{eu}(\tau) = 0, \;\; \tau > 0, \quad \text{and} \quad R_{eu}(\tau) \neq 0, \;\; \tau \leq 0$$

Such statement can be used for detection of feedback

References

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