System Identification

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Part IV

Correlation analysis

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Motivation 1

Why other techniques than transient analysis?

Transient analysis of step and impulse responses:

- Only works for a few system orders
- Must usually be done (semi-)manually
- Gives a rough, heuristic model of the system

The upcoming system identification methods:

- Work for arbitrary system orders
- Provide fully implementable, automatic algorithms
- Have solution accuracy guarantees (under appropriate conditions)

Motivation 2

Why correlation analysis?

- Closest to transient analysis (model = impulse response)
- True nonparametric model
- “Simple” general identification technique

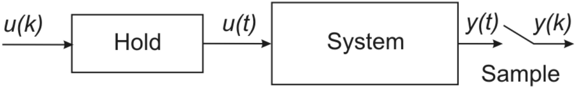
Classification

Recall **Types of models** from Part I:

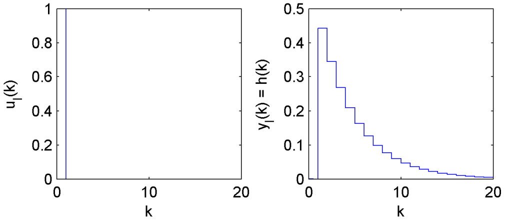
1. Mental or verbal models
2. Graphs and tables (nonparametric)
3. Mathematical models, with two subtypes:
   - First-principles, analytical models
   - Models from system identification

Correlation analysis is truly a nonparametric method; it produces an *impulse response model*.

Recall: discrete-time model



Discrete-time impulse response



Discrete-time, unit impulse signal:

$$u_{\mathrm{I}}(k) = \begin{cases} 1 & k = 0 \\ 0 & k > 0 \end{cases}$$

(does not have area 1, so it's different from the discrete-time realization of the continuous-time impulse!)

Discrete-time impulse response:

$$y_I(k) = h(k), \quad k \geq 0$$

$h(k), k \geq 0$ is also called the weighting function of the system.

Convolution

The (disturbance-free) response to an arbitrary signal $u(k)$ is the *convolution* of the input and the impulse response:

$$y(k) = \sum_{j=0}^{\infty} h(j)u(k-j)$$

Intuition: Consider a signal $\tilde{u}_j(k)$ equal to $u(j)$ at $k = j$, and 0 elsewhere; just a shifted and scaled unit impulse:

$$\tilde{u}_j(k) = u(j)u_{\mathrm{I}}(k-j)$$

So, the response to $\tilde{u}_j(k)$ is a shifted and scaled impulse response:

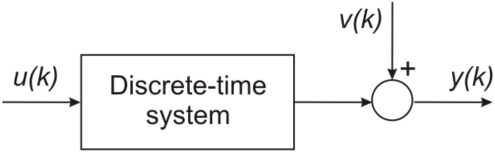
$$\tilde{y}_j(k) = u(j)h(k-j)$$

Now, $u(k)$ is the superposition of all signals $\tilde{u}_j$, and due to linearity:

$$y(k) = \sum_{j=0}^{k} \tilde{y}_j(k) = \sum_{j=0}^{k} u(j)h(k-j) = \sum_{j=0}^{k} h(j)u(k-j) = \sum_{j=0}^{\infty} h(j)u(k-j)$$

where zero initial conditions were assumed, i.e. $u(j) = 0 \forall j < 0$.

Impulse-response model



$$\boxed{y(k) = \sum_{j=0}^{\infty} h(j)u(k-j) + v(k)}$$

Includes, in addition to the ideal model, a disturbance term $v(k)$.

Assumptions

Assumptions

1. The input $u(k)$ is a stationary stochastic process.
2. The input $u(k)$ and the disturbance $v(k)$ are independent.

Recall:

- Independence of random variables.
- Stationary stochastic process: constant mean at every time step, covariance only depends on difference between time steps and not on absolute time.

Covariance functions

The covariance functions are defined as follows:

$$\begin{aligned} r_{yu}(\tau) &= \mathrm{E}\left\{y(k+\tau)u(k)\right\} \\ r_{u}(\tau) &= \mathrm{E}\left\{u(k+\tau)u(k)\right\} \end{aligned}$$

Note: These quantities are true covariances only when the input and output are zero-mean, so if they are not, then the means must be subtracted prior to applying the algorithm.

Relationship of covariances and impulse response

If there were no disturbance, then:

$$
\begin{aligned}
r_{yu}(\tau) &= \mathrm{E}\left\{y(k+\tau)u(k)\right\} \\
&= \mathrm{E}\left\{\left[\sum_{j=0}^{\infty} h(j)u(k+\tau-j)\right] u(k)\right\} \\
&= \sum_{j=0}^{\infty} h(j)\mathrm{E}\left\{u(k+\tau-j)u(k)\right\} = \sum_{j=0}^{\infty} h(j)r_u(\tau-j)
\end{aligned}
$$

The errors coming from the disturbance are dealt with later, implicitly, using linear regression.

Impulse response identification

Writing the covariance relationship for all τ:

$$r_{yu}(0) = \sum_{j=0}^{\infty} h(j) r_u(-j) = h(0)r_u(0) + h(1)r_u(-1) + h(2)r_u(-2) + \dots$$

$$r_{yu}(1) = \sum_{j=0}^{\infty} h(j) r_u(1-j) = h(0)r_u(1) + h(1)r_u(0) + h(2)r_u(-1) + \dots$$

$$\dots$$

we obtain (in principle) an infinite system of linear equations:

- Coefficients $r_u(\tau)$, $r_{yu}(\tau)$.
- Unknowns $h(0), h(1), \dots$: solution of the system.

Next, a practical algorithm working with finite data is given.

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Covariances from data

Consider we are given signals $u(k), y(k)$ with $k = 1, \ldots, N$.
We have, for positive τ:

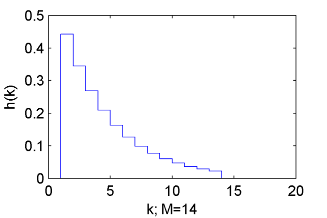
$$\begin{aligned} r_u(\tau) &= \mathrm{E}\{u(k+\tau)u(k)\} \\ &\approx \boxed{\frac{1}{N-\tau}\sum_{k=1}^{N-\tau} u(k+\tau)u(k)} \\ &=: \widehat{r}_u(\tau), \qquad \forall \tau \geq 0 \end{aligned}$$

and $\widehat{r}_u(-\tau) = \widehat{r}_u(\tau)$ for negative values, as u is a stationary process.

For positive and negative τ:

$$\begin{aligned} r_{yu}(\tau) &= \mathrm{E}\{y(k+\tau)u(k)\} \\ &\approx \boxed{\frac{1}{N-|\tau|}\sum_{k=1-\min\{\tau,0\}}^{N-\max\{\tau,0\}} y(k+\tau)u(k)} \\ &=: \widehat{r}_{yu}(\tau), \qquad \forall \tau \geq 0 \end{aligned}$$

Finite impulse response model



Impose the condition $h(k) = 0$ for $k \geq M$. We obtain the finite impulse response (FIR) model:

$$y(k) = \sum_{j=0}^{M-1} h(j)u(k-j) + v(k)$$

The covariance relationship is similarly truncated:

$$r_{yu}(\tau) = \sum_{j=0}^{M-1} h(j)r_u(\tau - j)$$

Note: M must be taken so that $MT_s \gg$ dominant time constants (or equivalently, the system is close to steady-state)

Linear system

Using $\widehat{r}_{yu}$, $\widehat{r}_u$ estimated from data, write the truncated equations for $\tau = 0, \ldots, T-1$ (keeping in mind that $\widehat{r}_u(-\tau) = \widehat{r}_u(\tau)$):

$$\begin{aligned}
\widehat{r}_{yu}(0) &= \sum_{j=0}^{M-1} h(j)\widehat{r}_u(-j) \\
&= h(0)\widehat{r}_u(0) + h(1)\widehat{r}_u(1) + \ldots + h(M-1)\widehat{r}_u(M-1) \\
\widehat{r}_{yu}(1) &= \sum_{j=0}^{M-1} h(j)\widehat{r}_u(1-j) \\
&= h(0)\widehat{r}_u(1) + h(1)\widehat{r}_u(0) + \ldots + h(M-1)\widehat{r}_u(M-2) \\
&\ldots \\
\widehat{r}_{yu}(T-1) &= \sum_{j=0}^{M-1} h(j)\widehat{r}_u(T-1-j) \\
&= h(0)\widehat{r}_u(T-1) + h(1)\widehat{r}_u(T-2) + \ldots + h(M-1)\widehat{r}_u(T-M)
\end{aligned}$$

– a linear system of T equations in M unknowns $h(0), \ldots, h(M-1)$.

Linear system (continued)

In matrix form:

$$\boxed{\begin{bmatrix} \hat{r}_{yu}(0) \\ \hat{r}_{yu}(1) \\ \vdots \\ \hat{r}_{yu}(T-1) \end{bmatrix} = \begin{bmatrix} \hat{r}_u(0) & \hat{r}_u(1) & \dots & \hat{r}_u(M-1) \\ \hat{r}_u(1) & \hat{r}_u(0) & \dots & \hat{r}_u(M-2) \\ \vdots & & & \\ \hat{r}_u(T-1) & \hat{r}_u(T-2) & \dots & \hat{r}_u(T-M) \end{bmatrix} \cdot \begin{bmatrix} h(0) \\ h(1) \\ \vdots \\ h(M-1) \end{bmatrix}}$$

Naively taking $T = M$ would give an exact system solution, but due to noise and disturbances this solution would be overfitted. So it is necessary to take $T > M$ (preferably, $T \gg M$).

Then we can apply the machinery of linear regression (see Part 3) to solve this problem.

Using the FIR model

Once the system has been solved for the estimated $\hat{h}$, we predict outputs with:

$$\boxed{\hat{y}(k) = \sum_{j=0}^{M-1} \hat{h}(j)u(k-j)}$$

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Special case: White noise input

Additional assumption

3. The input $u(k)$ is zero-mean white noise.

Then $r_u(\tau) = 0$ whenever $\tau \neq 0$ (since white noise is uncorrelated), and $r_{yu}(\tau) = \sum_{j=0}^{\infty} h(j) r_u(\tau - j)$ simplifies to:

$$r_{yu}(\tau) = h(\tau) r_u(0)$$

leading to the easy algorithm:

$$\hat{h}(\tau) = \frac{\widehat{r}_{yu}(\tau)}{\widehat{r}_u(0)}$$

Simplified guarantee

Theorem

In the white-noise case, as the number of data points N grows to infinity, the estimates $\widehat{h}(\tau)$ converge to the true values $h(\tau)$.

Remark: This type of property, where the true solution is obtained in the limit of infinite data, is called *consistency*.

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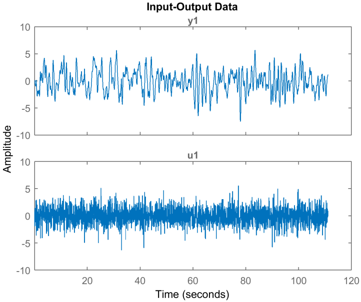
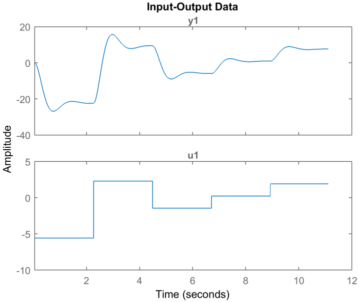
Experimental data

Consider we are given the following, separate, identification and validation data sets.

`plot(id);` and `plot(val);`





Note the identification input is white noise, while the validation input is not. There are 1100 samples in the identification data.

Applying correlation analysis

`fir = cra(id, M, 0);` or `fir = cra(id, M, 0, plotlevel);`

Arguments:

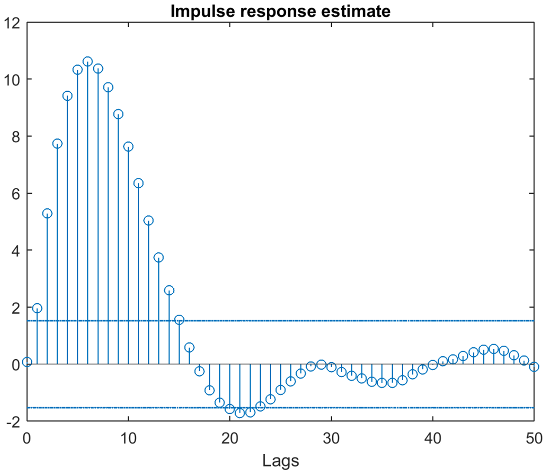
1. Identification data.
2. FIR length M, here it is set to 45.
3. Third argument 0 means no *input whitening* is performed.

Dealing with non-ideal inputs:

- If input is not zero-mean, pass the data through `detrend` to remove the means.
- If input is not white noise, the third argument should be left to default (by not specifying it or setting it to an empty matrix), which means input whitening is performed.

Applying correlation analysis (continued)

By default (or with `plotlevel=1`) the FIR parameters are shown with a 99% confidence interval.

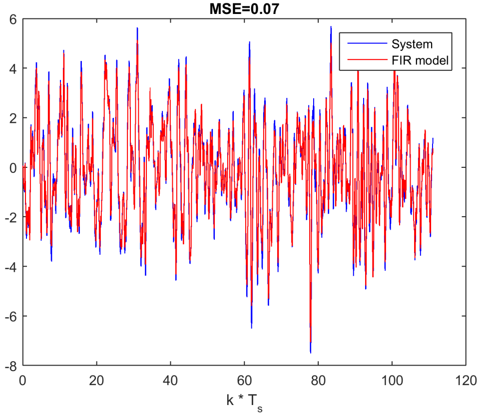


`plotlevel=2` also produces the covariance functions.

Results on the identification data

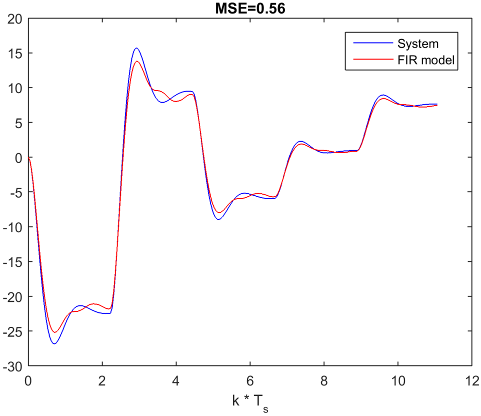
```
yhat = conv(fir, id.u); yhat = yhat(1:length(id.u));
```

To simulate the FIR model, a *convolution* between the FIR parameters and the input is performed. The simulated output is longer than needed so we cut it off at the right length.



Validation of the FIR model

```
yhat = conv(fir, val.u); yhat = yhat(1:length(val.u));
```



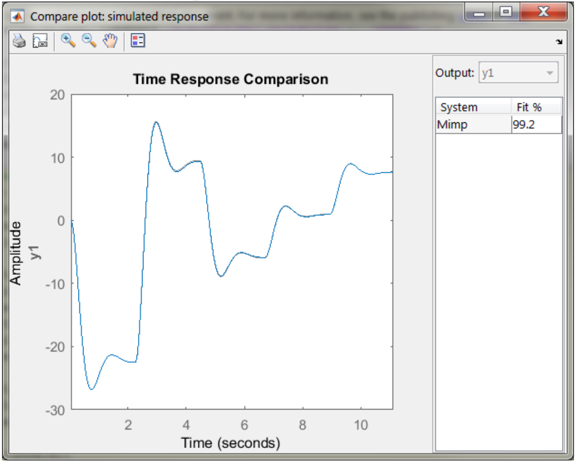
Results OK, not great.

Alternative: `impulseest` function

`model = impulseest(id, M);` or `model = impulseest(id);`

Uses a more involved algorithm than the one studied in the lectures.

`compare(mod, val);`



The fit is very good.