

Identification of Linear Systems in the Presence of Nonlinear Distortions

A Frequency Domain Approach

Johan Schoukens*
Belgian Francqui Chair
Université Libre de Bruxelles

*Vrije universiteit Brussel

Today's lesson

Frequency Response Function Measurements (February 8)

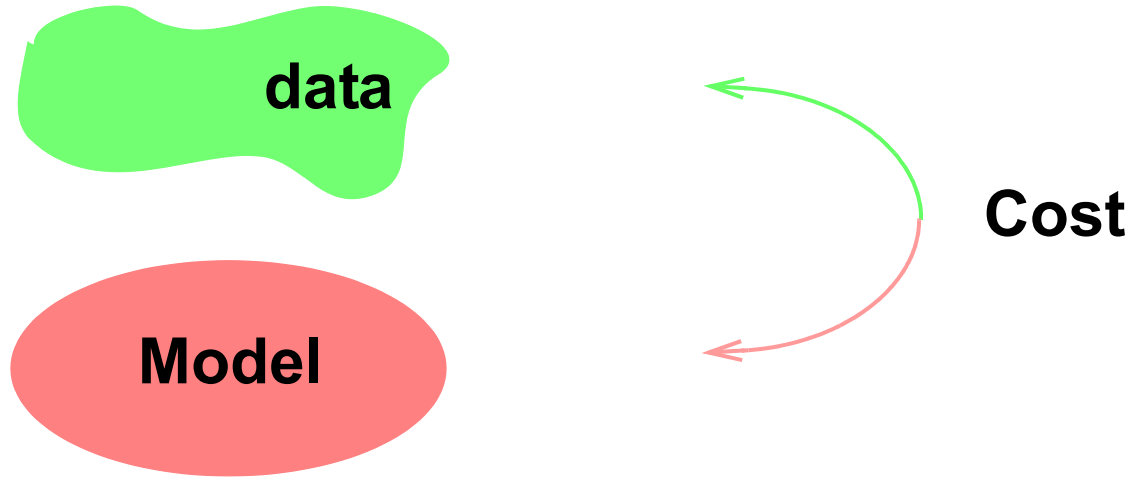
Impact of Nonlinear Distortions on the Linear Framework (February 15)

System Identification (February 22)

Identification of Linear Systems (March 1)

Identification of Nonlinear Systems (March 8)

System identification



Goal

A statistical framework

Outline

A motivating example: why do *you* need system identification?!

Characterizing estimators

Basic steps of the identification process

A statistic approach to system identification

Identification in the presence of 'input' and 'output' noise

Why do you need identification methods?

A simple experiment



Why do you need identification methods?

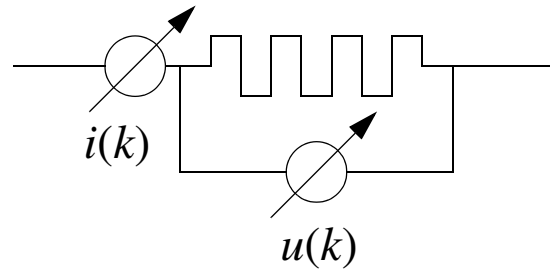
A simple experiment

Multiple measurements lead to conflicting results.

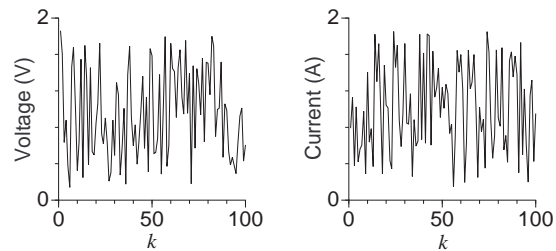
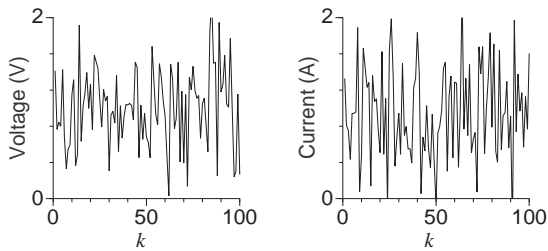
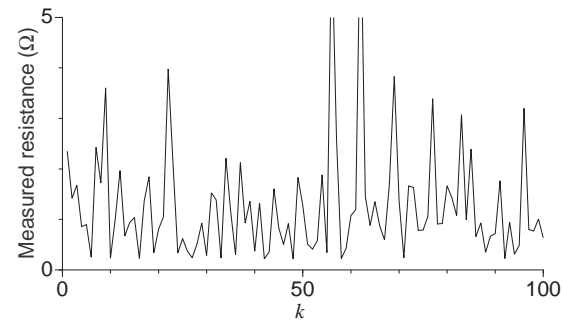
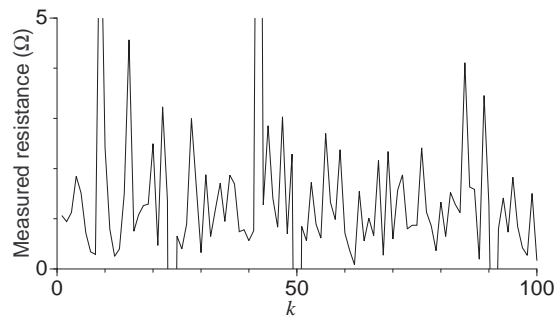
How to combine all this information?

Why do you need identification methods

Measurement of a resistance



2 sets of measurements



Group A

Group B

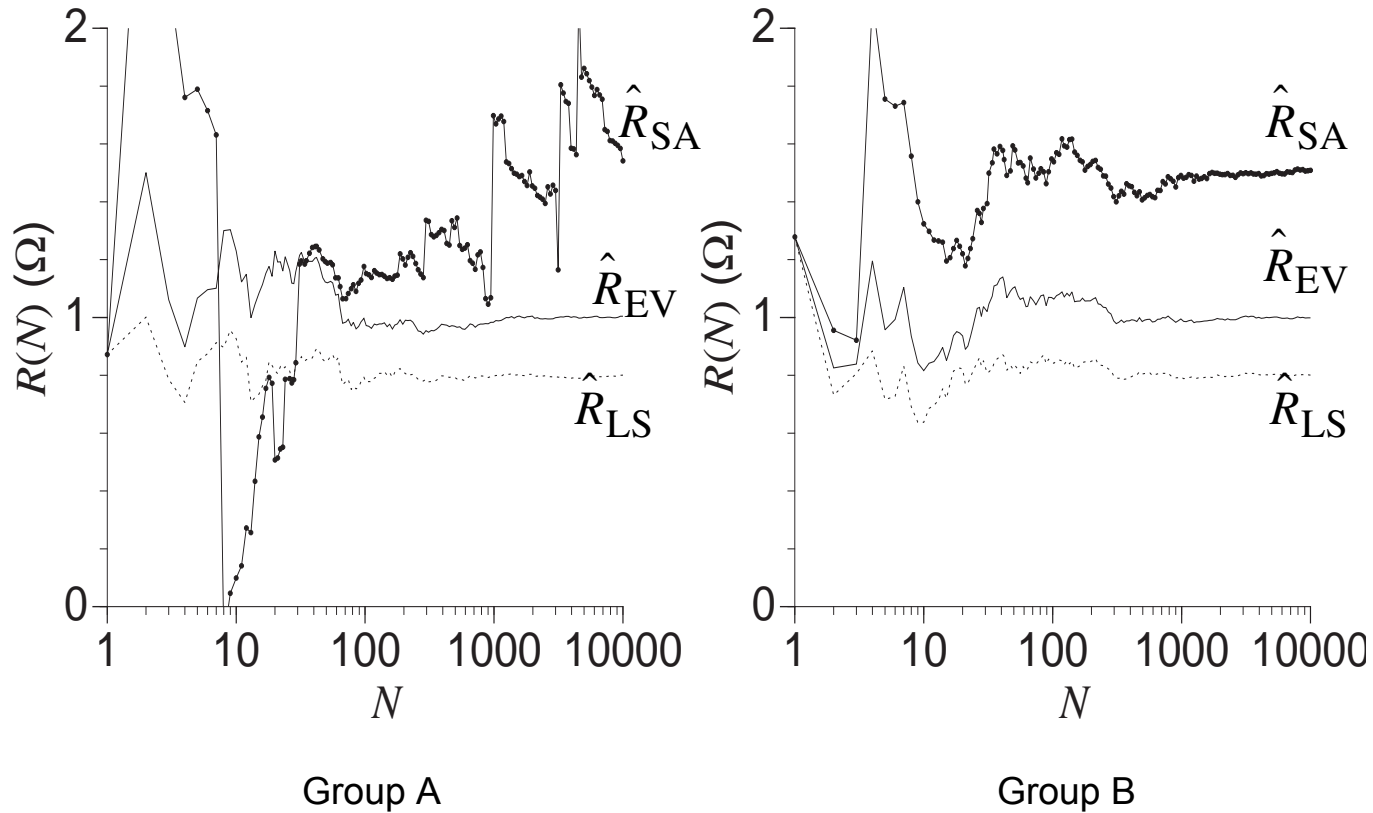
3 different estimators

$$\hat{R}_{SA}(N) = \frac{1}{N} \sum_{k=1}^N \frac{u(k)}{i(k)}$$

$$\hat{R}_{LS}(N) = \frac{\frac{1}{N} \sum_{k=1}^N u(k)i(k)}{\frac{1}{N} \sum_{k=1}^N i(k)^2}$$

$$\hat{R}_{EV}(N) = \frac{\frac{1}{N} \sum_{k=1}^N u(k)}{\frac{1}{N} \sum_{k=1}^N i(k)}$$

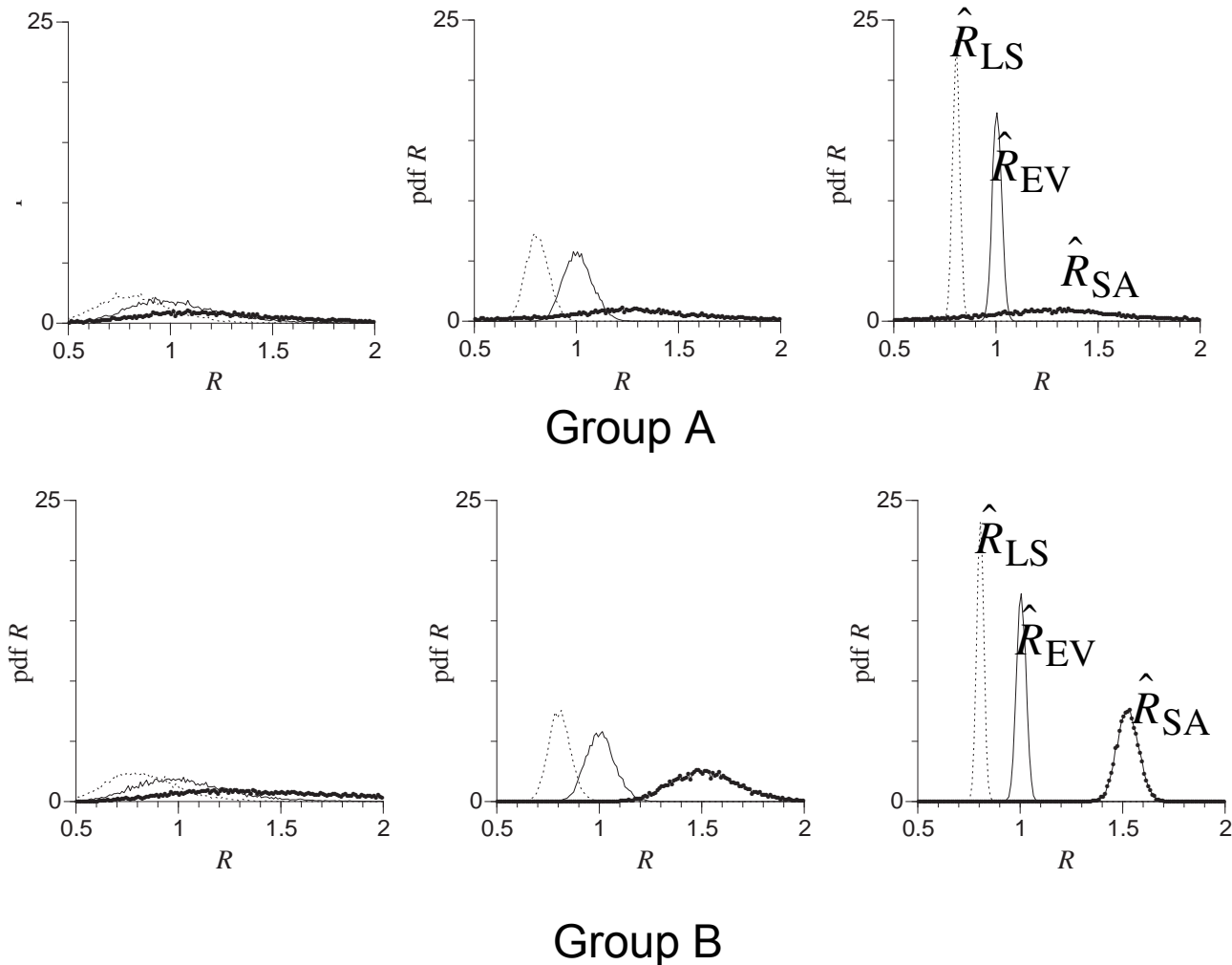
and their results



Remarks

- variations decrease as function of N , except for \hat{R}_{SA}
- the asymptotic values are different
- \hat{R}_{SA} behaves 'strange'

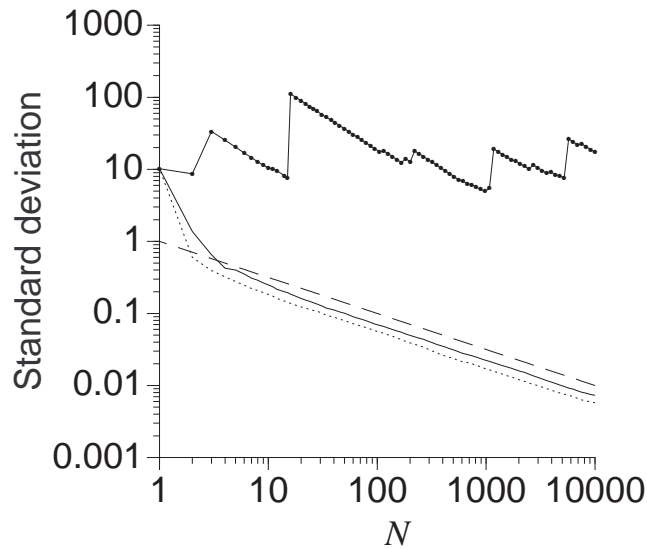
Repeating the experiments.



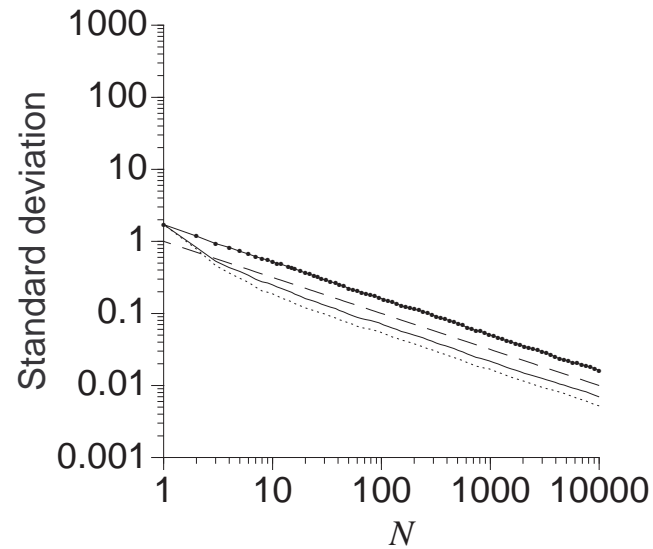
Observed pdf of $\hat{R}(N)$ for both groups, from the left to the right $N = 10, 100, \text{ and } 1000$

- the distributions become more concentrated around their limit value
- \hat{R}_{SA} behaves 'strange' for group A

Repeating the experiments



Group



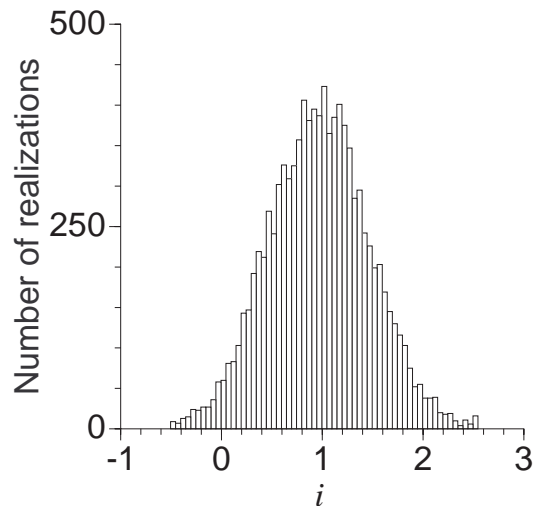
Group B

Standard deviation of $\hat{R}(N)$

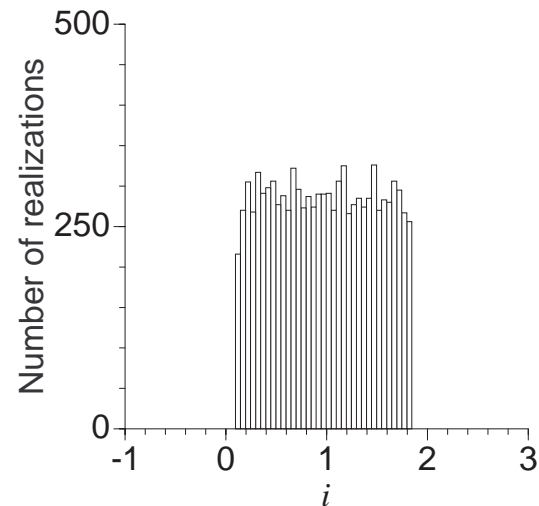
full dotted line: \hat{R}_{SA} , dotted line: \hat{R}_{LS} , full line: \hat{R}_{EV} , dashed line $1/\sqrt{N}$.

- the standard deviation decrease in \sqrt{N}
- the uncertainty also depends on the estimator

Strange behaviour of \hat{R}_{SA} for group A



Group A



Group B

Histogram of the current measurements.

- The current takes negative values for group A
- the estimators tend to a normal distribution
even when the noise behaviour is completely different

Simplified analysis

Why do the asymptotic values depend on the estimator?

Can we explain the behaviour of the variance?

Why does the \hat{R}_{SA} estimator behave strange for group A?

More information is needed to answer these questions

Noise model of the measurements

$$i(k) = i_0 + n_i(k) \quad u(k) = u_0 + n_u(k)$$

Assumptions:

$n_i(k)$ and $n_u(k)$ are:

- mutually independent
- zero mean
- independent and identically distributed
- have a symmetric distribution
- variance σ_u^2 and σ_i^2 .

Statistical tools

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N x(k) = 0$$

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N x(k)^2 = \sigma_x^2$$

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N x(k)y(k) = 0$$

Asymptotic value of \hat{R}_{LS}

$$\begin{aligned}\lim_{N \rightarrow \infty} \hat{R}_{LS}(N) &= \lim_{N \rightarrow \infty} \left(\sum_{k=1}^N u(k)i(k) \right) / \left(\sum_{k=1}^N i^2(k) \right) \\ &= \lim_{N \rightarrow \infty} \frac{\frac{1}{N} \sum_{k=1}^N (u_0 + n_u(k))(i_0 + n_i(k))}{\frac{1}{N} \sum_{k=1}^N (i_0 + n_i(k))^2}\end{aligned}$$

Or

$$\begin{aligned}\lim_{N \rightarrow \infty} R_{LS}(N) &= \\ \lim_{N \rightarrow \infty} \frac{u_0 i_0 + \frac{u_0}{N} \sum_{k=1}^N n_i(k) + \frac{i_0}{N} \sum_{k=1}^N n_u(k) + \frac{1}{N} \sum_{k=1}^N n_u(k)n_i(k)}{i_0^2 + \frac{1}{N} \sum_{k=1}^N n_i^2(k) + \frac{2i_0}{N} \sum_{k=1}^N n_i(k)}\end{aligned}$$

And finally

$$\lim_{N \rightarrow \infty} \hat{R}_{LS}(N) = \frac{u_0 i_0}{i_0^2 + \sigma_i^2} = R_0 \frac{1}{1 + \sigma_i^2 / i_0^2}$$

It converges to the wrong value!!!

Asymptotic value of \hat{R}_{EV}

$$\begin{aligned}\lim_{N \rightarrow \infty} \hat{R}_{EV}(N) &= \lim_{N \rightarrow \infty} \left(\sum_{k=1}^N u(k) \right) / \left(\sum_{k=1}^N i(k) \right) \\ &= \lim_{N \rightarrow \infty} \frac{\frac{1}{N} \sum_{k=1}^N (u_0 + n_u(k))}{\frac{1}{N} \sum_{k=1}^N (i_0 + n_i(k))} \\ &= \left(\lim_{N \rightarrow \infty} \frac{u_0 + \frac{1}{N} \sum_{k=1}^N n_u(k)}{i_0 + \frac{1}{N} \sum_{k=1}^N n_i(k)} \right) \\ &= R_0\end{aligned}$$

It converges to the exact value!!!

Asymptotic value of \hat{R}_{LS}

$$\hat{R}_{SA}(N) = \frac{1}{N} \sum_{k=0}^N \frac{u(k)}{i(k)} = \frac{1}{N} \sum_{k=0}^N \frac{u_0 + n_u(k)}{i_0 + n_i(k)} = \frac{1}{N} \frac{u_0}{i_0} \sum_{k=0}^N \frac{1 + n_u(k)/u_0}{1 + n_i(k)/i_0}$$

The series expansion exist only for small noise distortions

$$\frac{1}{1+x} = \sum_{l=0}^{\infty} (-1)^l x^l \text{ for } |x| < 1$$

Group A: The expected value does not exist for the data of group A.

The estimator does not converge.

Group B: For group B the series converges and

$$\lim_{N \rightarrow \infty} \hat{R}_{SA}(N) \approx R_0 \left(1 + \frac{\sigma_i^2}{i_0^2} \right)$$

The estimator converges to the wrong value!!

Variance expressions

First order approximation

$$\sigma_{\hat{R}_{LS}}^2(N) \approx \sigma_{\hat{R}_{EV}}^2(N) \approx \sigma_{\hat{R}_{SA}}^2(N) \approx \frac{R_0^2}{N} \left(\frac{\sigma_u^2}{2} + \frac{\sigma_i^2}{i_0} \right)$$

- variance decreases in $1/N$
- variance increases with the noise
- for low noise levels, all estimators have the same uncertainty

----> **Experiment design**

Cost function interpretation

The previous estimates match the model $u = Ri$ as good as possible on the data.

A criterion to express the goodness of the fit is needed ----> Cost function interpretation.

$\hat{R}_{SA}(N)$

$$V_{SA}(R) = \frac{1}{N} \sum_{k=1}^N (R(k) - R)^2.$$

$\hat{R}_{LS}(N)$

$$V_{LS}(R) = \frac{1}{N} \sum_{k=1}^N (u(k) - Ri(k))^2$$

$\hat{R}_{EV}(N)$

$$V_{EV}(R, i_0, u_0) = \frac{1}{N} \left(\sum_{k=1}^N \frac{(u(k) - u_0)^2}{\sigma_u^2} + \sum_{k=1}^N \frac{(i(k) - i_0)^2}{\sigma_i^2} \right) \text{ subject to } u_0 = Ri_0$$

Conclusion

- A simple problem
- Many solutions
- How to select a good estimator?
- Can we know the properties in advance?

Need for a general framework !!

Outline

A motivating example: why do *you* need system identification?!

Characterizing estimators

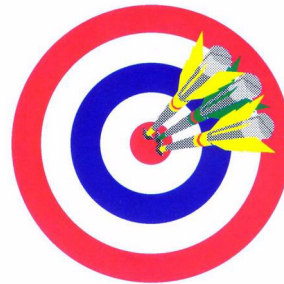
Basic steps of the identification process

A statistic approach to system identification

Identification in the presence of 'input' and 'output' noise

Characterizing estimators

Location properties: are the parameters concentrated around the 'exact value' ?



Dispersion properties: is the uncertainty small or large?

Location properties

unbiased and consistent estimators

Unbiased estimates

the mean value equals the exact value

Definition

An estimator $\hat{\theta}$ of the parameters θ_0 is unbiased if $E\{\hat{\theta}\} = \theta_0$, for all true parameters θ_0 . Otherwise it is a biased estimator.

Asymptotic unbiased estimates: unbiased for $N \rightarrow \infty$

Example

i) The sample mean

$$\hat{u}(N) = \frac{1}{N} \sum_{k=1}^N u(k)$$

Unbiased?

$$E \{ \hat{u}(N) \} = \frac{1}{N} \sum_{k=1}^N E \{ u(k) \} = \frac{1}{N} \sum_{k=1}^N u_0 = u_0$$

ii) The sample variance

$$\hat{\sigma}_u^2(N) = \frac{1}{N} \sum_{k=1}^N (u(k) - \hat{u}(N))^2$$

Unbiased?

$$E \{ \hat{\sigma}_u^2(N) \} = \frac{N-1}{N} \sigma_u^2$$

Alternative expression

$$\frac{1}{N-1} \sum_{k=1}^N (u(k) - \hat{u}(N))^2$$

Example cont'd

$$\hat{\sigma}_1^2 = \frac{1}{N-1} \sum_{k=1}^N (u(k) - \hat{u}(N))^2 \quad \text{and} \quad \hat{\sigma}_2^2 = \frac{1}{N} \sum_{k=1}^N (u(k) - \hat{u}(N))^2$$

bias $\hat{\sigma}_1^2 = 0$, and bias $\hat{\sigma}_2^2 = \frac{\sigma^2}{N}$

variance $\hat{\sigma}_1^2 > \text{variance } \hat{\sigma}_2^2$

RMS error $\hat{\sigma}_1^2 > \text{RMS error } \hat{\sigma}_2^2$

Best choice?

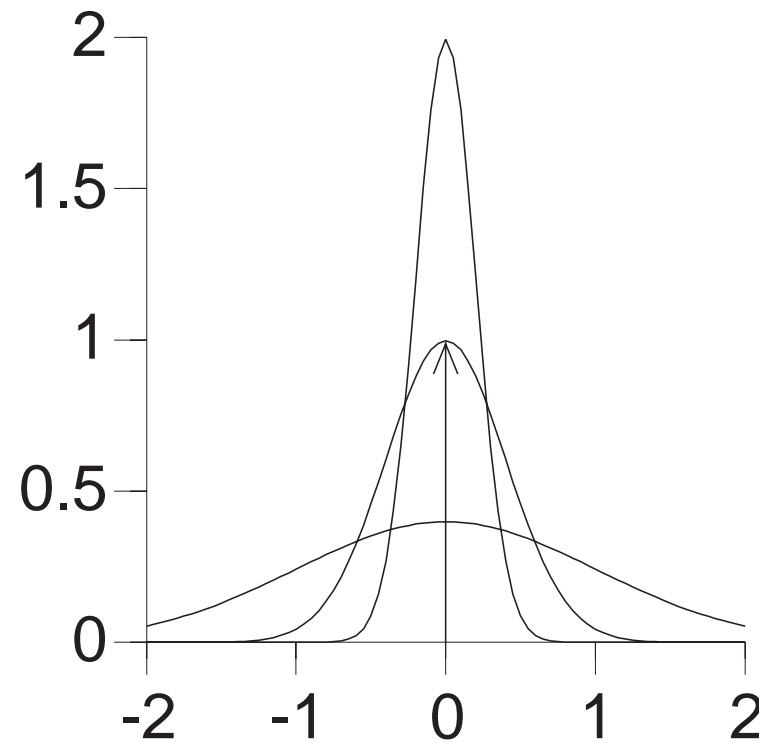
Consistent estimates

Consistent estimates: the probability mass gets concentrated around the exact value

$$\lim_{N \rightarrow \infty} \text{Prob}(|\hat{\theta}(N) - \theta_0| > \delta > 0) = 0$$

or

$$\text{plim}_{N \rightarrow \infty} \hat{\theta}(N) = \theta_0$$



Consistency

properties

$$\text{plim } f(a) = f(\text{plim } a)$$

$$\text{plim } ab = \text{plim } a \text{ plim } b \text{ if all plim exist}$$

Example

$$\begin{aligned}\text{plim}_{N \rightarrow \infty} \hat{R}_{EV}(N) &= \text{plim}_{N \rightarrow \infty} \frac{\frac{1}{N} \sum_{k=1}^N u(k)}{\frac{1}{N} \sum_{k=1}^N i(k)} \\ &= \frac{\text{plim}_{N \rightarrow \infty} \left(\frac{1}{N} \sum_{k=1}^N u(k) \right)}{\text{plim}_{N \rightarrow \infty} \left(\frac{1}{N} \sum_{k=1}^N i(k) \right)} \\ &= \frac{u_0}{i_0} \\ &= R_0\end{aligned}$$

Dispersion properties

efficient estimators

- Mostly the covariance matrix is used, however alternatives like percentiles exist.
- For a given data set, there exists a minimum bound on the covariance matrix:

the Cramér-Rao lower bound.

$$CR(\theta) = Fi^{-1}(\theta_0)$$

with

$$Fi(\theta_0) = E \left\{ \left(\frac{\partial}{\partial \theta} l(Z|\theta) \right)^T \left(\frac{\partial}{\partial \theta} l(Z|\theta) \right) \right\} = -E \left\{ -\frac{\partial^2}{\partial \theta^2} l(Z|\theta) \right\}.$$

The derivatives are calculated in $\theta = \theta_0$

The likelihood function

- 1) Consider the measurements $Z \in \mathbb{R}^N$
- 2) Z is generated by a hypothetical, exact model with parameters θ_0
- 3) Z is disturbed by noise --> stochastic variables
- 4) Consider the probability density function $f(Z|\theta_0)$ with

$$\int_{z \in \mathbb{R}^N} f(Z|\theta_0) dZ = 1.$$

- 5) Interpret this relation conversely, viz:

how likely is it that a specific set of measurements $Z = Z_m$ are generated by a system with parameters θ ?

--> Measurements given

Model parameters as the free variables:

$L(Z_m|\theta) = f(Z = Z_m|\theta)$, with θ the free variables

$L(Z_m|\theta)$: **likelihood function.**

Interpretation of the Cramér-Rao lower bound

Model $y_0 = f(u_0, \theta)$

Measurement $y = y_0 + n_y$ and $n_y \sim N(0, \sigma^2)$

Likelihood function $L(y|\theta) = f_n(y|\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-f(u_0, \theta))^2}{2\sigma^2}}$

Loglikelihood function $l(y|\theta) = -\frac{1}{2}\log(2\pi\sigma^2) - \frac{(y-f(u_0, \theta))^2}{2\sigma^2}$

$$\frac{\partial l}{\partial \theta} = -\frac{(y-f(u_0, \theta))}{\sigma^2} \frac{\partial}{\partial \theta} f(u_0, \theta)$$

Information matrix

$$\begin{aligned} Fi(\theta_0) &= E\left\{\left(\frac{\partial l}{\partial \theta}\right)^T \left(\frac{\partial l}{\partial \theta}\right)\right\} \\ &= E\left\{\frac{(y-f(u_0, \theta))^2}{\sigma^4} \left(\frac{\partial}{\partial \theta} f(u_0, \theta)\right)^2\right\} \\ &= \frac{1}{\sigma^2} \left(\frac{\partial}{\partial \theta} f(u_0, \theta)\right)^2 \end{aligned}$$

Characterizing estimators

- Goal asymptotic analysis
 - what happens with the estimate if more data are gathered?
 - hypothesis: asymptotic behaviour reflects finite sample behaviour
 - true finite sample behaviour is in general very difficult to establish
(exception: linear least squares)
- Consistency
 - convergence in *stochastic* sense to the true value
 - does not exclude divergence for some realisations
 - guarantees with high probability that estimate is close to true value
 - consistency does not imply asymptotic unbiasedness
 - proof: law of large numbers
- Asymptotic unbiasedness
 - asymptotically the expected value equals the true value
 - does not guarantee that the estimate is close to the true value
 - in general very difficult to verify (exception: linear least squares)
- Asymptotic normality
 - allows to construct uncertainty bounds with a given confidence level
 - proof: linearisation around limit value + central limit theorem

Characterizing estimators (Cont'd)

- Asymptotic variance
 - measure of the convergence rate
 - construction of uncertainty bounds
 - proof: linearisation around limit value
- Asymptotic efficiency
 - minimal uncertainty within class of asymptotically unbiased estimators
 - in practice applied to class of consistent estimators
 - Cramér-Rao lower bound does not always exist
 - or may be too conservative
 - proof: comparison asymptotic variance with Cramér-Rao lower bound
- Robustness
 - sensitivity (asymptotic) properties to the noise assumptions
 - proof: validity law of large numbers and central limit theorem
 - under relaxed noise assumptions

Outline

A motivating example: why do *you* need system identification?!

Characterizing estimators

Basic steps of the identification process

A statistic approach to system identification

Identification in the presence of 'input' and 'output' noise

Basic steps in identification

1) collect the information: experiment setup

2) select a model

parametric >< nonparametric models

white>< black box models

linear><nonlinear models

linear -in-the-parameters><nonlinear-in-the-parameters

$$\varepsilon = y - (a_1 u + a_2 u^2), \quad \varepsilon(\omega) = Y(\omega) - \frac{a_0 + a_1 j\omega}{b_0 + b_1 j\omega} U(\omega)$$

3) match the model to the data

select a cost function

LS, WLS, MLE, Bayes estimation

4) validation

does the model explain the data?

can it deal with new data?

Remark

this scheme is not only valid for the classical identification theory.
It also applies to neural nets, fuzzy logic, ...

Outline

A motivating example: why do *you* need system identification?!

Characterizing estimators

Basic steps of the identification process

A statistic approach to system identification

Identification in the presence of 'input' and 'output' noise

A statistical framework: choice of the cost functions

$$y_0 = G(u, \theta_0), y = y_0 + n_y, e = y - G(u, \theta_0)$$

Least squares estimation

$$V_{\text{LS}}(\theta) = \frac{1}{N} \sum_{k=1}^N e^2(k, \theta)$$

Weighted least squares estimation

$$V_{\text{WLS}}(\theta) = \frac{1}{N} e(\theta)^T W e(\theta)$$

Maximum likelihood estimation

$$f(y|\theta_0) = f_{n_y}(y - G(u, \theta_0))$$

$$\theta_{\text{ML}} = \underset{\theta}{\operatorname{argmax}} f(y_m|\theta)$$

Least squares: principle

Model

$$y_0(k) = g(u_0(k), \theta)$$

with k the measurement index, and

$$y(k) \in \mathbb{R}, u(k) \in \mathbb{R}^{1 \times M}, \theta \in \mathbb{R}^{n_\theta \times 1}$$

Measurements

$$y(k) = y_0(k) + n_y(k)$$

Match model and measurements

Choose:

$$e(k, \theta) = y(k) - y(k, \theta),$$

with $y(k, \theta)$ the modelled output.

Then

$$\hat{\theta}_{LS} = \arg \min_{\theta} V_{LS}(\theta),$$

with

$$V_{LS}(\theta) = \frac{1}{N} \sum_{k=1}^N e^2(k, \theta)$$

Least squares: special case model that is linear-in-the-parameters

$$y_0 = K(u_0)\theta_0$$

$$e(\theta) = y - K(u)\theta, \quad K = \frac{\partial e}{\partial \theta}$$

$$\hat{\theta}_{\text{LS}} = (K^T K)^{-1} K^T y$$

Properties

$$\hat{\theta}_{\text{LS}} = (K^T K)^{-1} K^T y$$

Noise assumptions

$$y = y_0 + n_y \text{ with } E[n_y] = 0$$

Bias?

$$\begin{aligned} E[\hat{\theta}_{\text{LS}}] &= E[(K^T K)^{-1} K^T y] \\ &= (K^T K)^{-1} K^T E[y] \\ &= (K^T K)^{-1} K^T y_0 \end{aligned}$$

Note that $y_0 = K\theta_0$

$$E[\hat{\theta}_{\text{LS}}] = (K^T K)^{-1} K^T K\theta_0 = \theta_0$$

Properties

$$\hat{\theta}_{\text{LS}} = (K^T K)^{-1} K^T y$$

Noise assumptions

$$y = y_0 + n_y \text{ with } E[n_y] = 0$$

Noise sensitivity?

$$\begin{aligned} \hat{\theta}_{\text{LS}} - \theta_0 &= (K^T K)^{-1} K^T n_y \\ &= \left(\frac{1}{N} K^T K \right)^{-1} \frac{1}{N} K^T n_y \end{aligned}$$

Note

$$\lim_{N \rightarrow \infty} \frac{1}{N} K^T n_y \sim N\left(0, K^T \frac{C_y}{N^2} K\right)$$

Covariance matrix

$$C_{\theta} = \left(\frac{1}{N} K^T K \right)^{-1} K^T \frac{C_y}{N^2} K \left(\frac{1}{N} K^T K \right)^{-1}$$

Asymptotical normal distributed

Example: weight of a loaf of bread

model

$$y_0 = \theta_0$$

measurements

$$y(k) = y_0 + n_y(k)$$

estimator

$$e(k) = y(k) - \theta$$

Standard formulation

$$y = K\theta + n_y \text{ with } K = (1, 1, \dots, 1)^T$$

Solution

$$\hat{\theta}_{\text{LS}} = (K^T K)^{-1} K^T y = \frac{1}{N} \sum_{k=1}^N y(k)$$

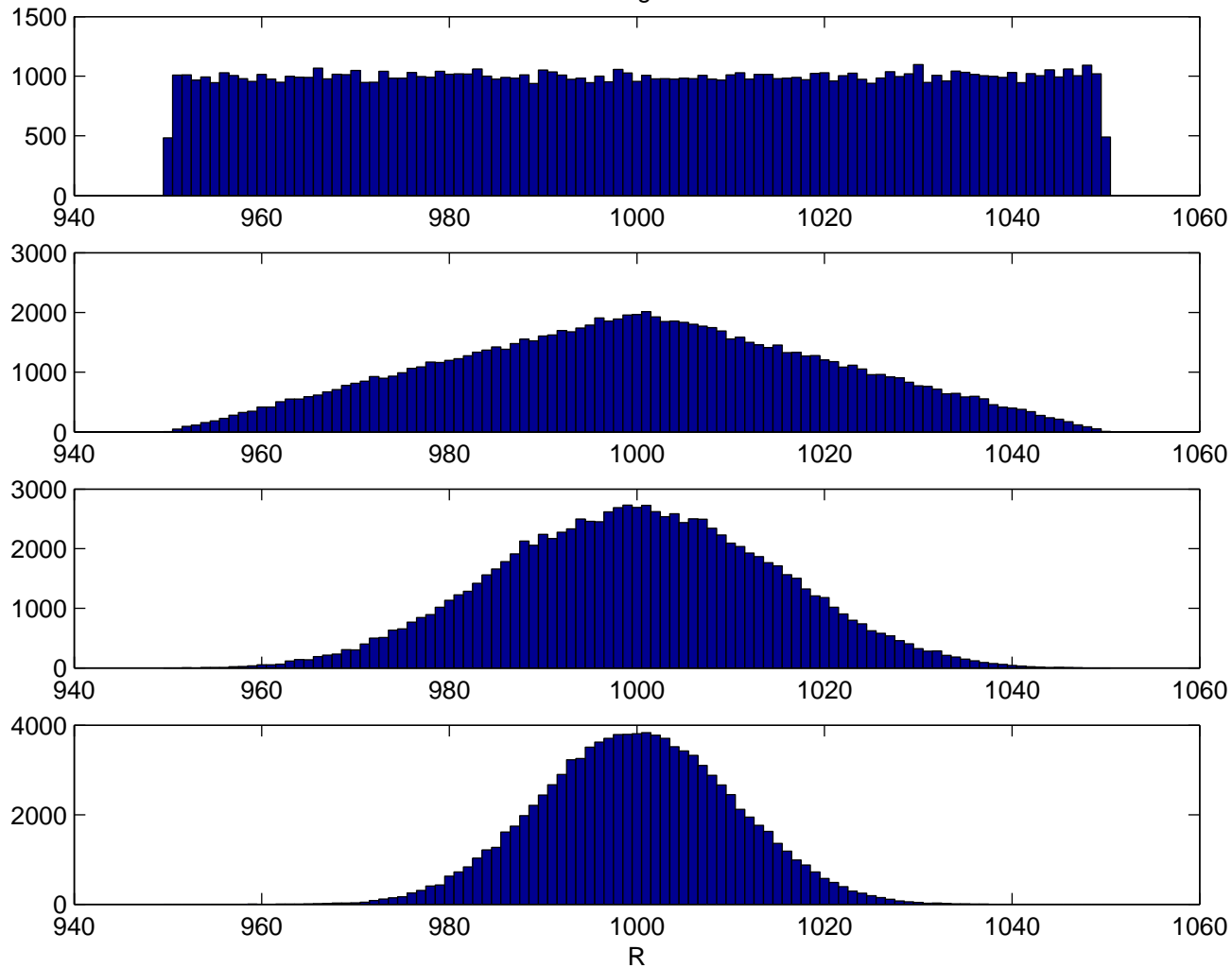
$$\sigma_{\hat{\theta}}^2 = \left(\frac{1}{N} K^T K \right)^{-1} K^T \frac{C_y}{N^2} K \left(\frac{1}{N} K^T K \right)^{-1} = \frac{\sigma_y^2}{N}, \text{ for white noise}$$

Example: weight of a loaf of bread (Cont'd)

measurements

$$y(k) = y_0 + n_y(k), k = 1, \dots, N$$

noise uniformly distributed $[-50, 50]$



Weighted least squares

Goal: bring your confidence in the measurements into the problem

Model

$$y_0(k) = g(u_0(k), \theta)$$

$$y(k) \in \mathbf{R}, u(k) \in \mathbf{R}^{1 \times M}, \theta \in \mathbf{R}^{n_\theta \times 1}$$

Measurements

$$y(k) = y_0(k) + n_y(k)$$

confidence in measurement k : $w(k)$

Match model and measurements

$$e(k, \theta) = y(k) - y(k, \theta),$$

Then

$$\hat{\theta}_{\text{LS}} = \arg \min_{\theta} V_{\text{LS}}(\theta),$$

with

$$V_{\text{WLS}}(\theta) = \frac{1}{N} \sum_{k=1}^N \frac{e^2(k, \theta)}{w(k)}$$

Weighted least squares (continued)

Generalization: use a full matrix to weight the measurements

define

$$e(\theta) = (e(1, \theta) \dots e(N, \theta))$$

consider a positive definite matrix W

Then

$$V_{\text{WLS}}(\theta) = \frac{1}{N} e(\theta)^T W^{-1} e(\theta)$$

Special choice:

$$W = E \{ n_y n_y^T \} = C_{n_y n_y} \in R^{N \times N}$$

This choice minimizes C_θ

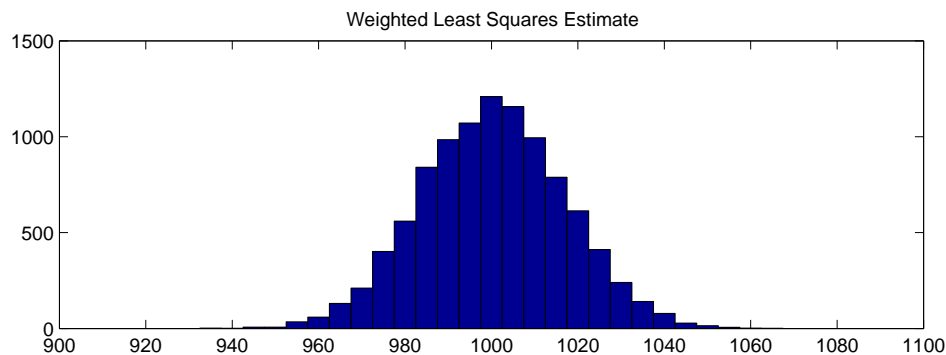
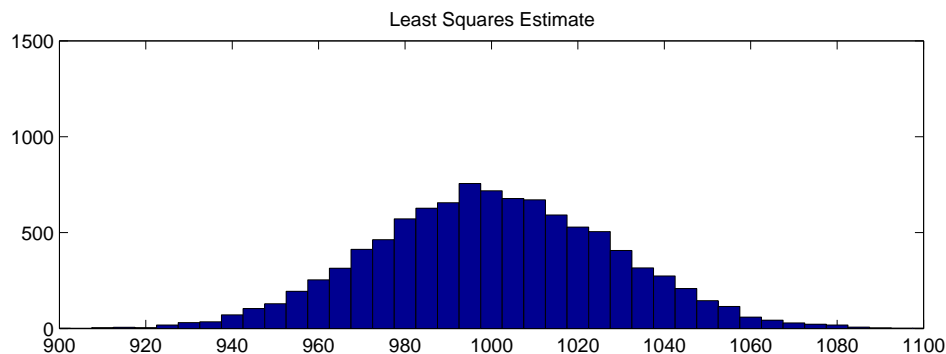
Example: resistor measurement, 2 voltmeters

$$i(k) = i_0(k)$$
$$u(k) = u_0(k) + n_u(k), \quad k = 1, 2, \dots, 100$$

i_0 uniformly distributed in $[0, 0.01]$

$$R_0 = 1000$$

Voltmeter 1: $N(0, \sigma_u^2=1)$, Voltmeter 2: $N(0, \sigma_u^2=3^2)$



Maximum likelihood estimation

Model

$$y_0(k) = g(u_0(k), \theta)$$

$$y(k) \in \mathbf{R}, u(k) \in \mathbf{R}^{1 \times M}, \theta \in \mathbf{R}^{n_\theta \times 1}$$

Measurements

$$y(k) = y_0(k) + n_y(k)$$

with f_{n_y} the pdf of the noise n_y

Match model and measurements

Choose the experiments such that the model becomes most likely:

Then

$$\theta_{\text{ML}} = \arg \max_{\theta} f(y_m | \theta, u)$$

with

$$f(y | \theta, u) = f_{n_y}(y - G(u, \theta))$$

Maximum likelihood: example weight of a loaf of bread

Model:

$$y_0 = \theta_0$$

Measurements:

$$y(k) = y_0 + n_y(k)$$

Additional information

The distribution f_y of n_y is normal with zero mean and standard deviation σ_y

Likelihood function:

$$f(y|\theta) = \frac{1}{\sqrt{2\pi\sigma_y^2}} e^{-\frac{(y-\theta)^2}{2\sigma_y^2}} = \frac{1}{\sqrt{2\pi\sigma_y^2}^N} e^{-\frac{1}{2\sigma_y^2} \sum_{k=1}^N (y(k) - \theta)^2}$$

Maximum likelihood estimator:

$$\hat{\theta}_{\text{ML}} = \frac{1}{N} \sum_{k=1}^N y(k)$$

Resistance example with Gaussian and Laplace noise

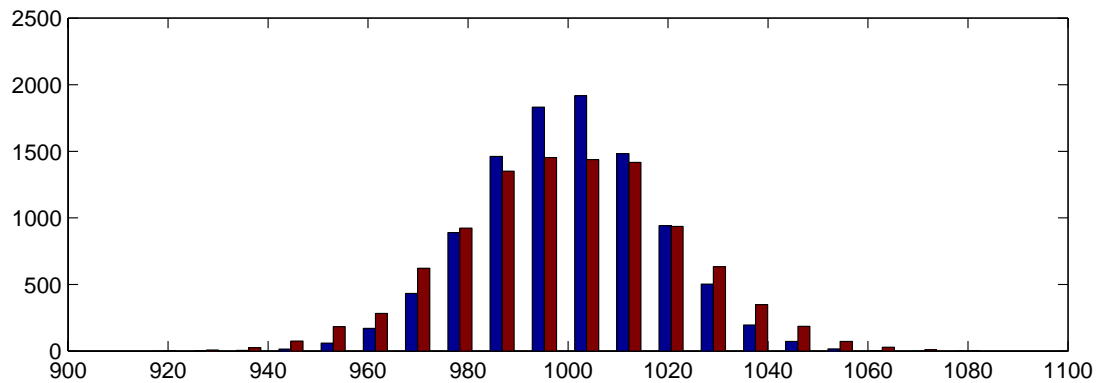
white Gaussian noise

$$\arg \min_R \sum_{k=1}^N |u(k) - Ri(k)|^2 \rightarrow \text{least squares}$$

white Laplace noise

$$\arg \min_R \sum_{k=1}^N |u(k) - Ri(k)| \rightarrow \text{least absolute values}$$

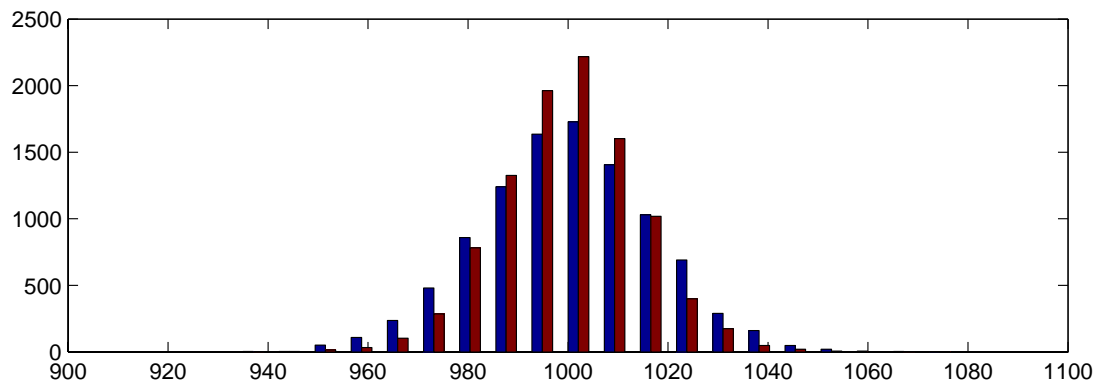
Gaussian



Least Squares

Least Abs Values

Laplace



Properties of the Maximum likelihood estimator

principle of invariance: if $\hat{\theta}_{\text{ML}}$ is a MLE of $\theta \in \mathbb{R}^{n_\theta}$, then $\hat{\theta}_g = g(\hat{\theta}_{\text{ML}})$ is a MLE of $g(\theta)$ where g is a function, $\hat{\theta}_g \in \mathbb{R}^{n_g}$ and $n_g \leq n_\theta$, with n_θ a finite number.

consistency: if $\hat{\theta}_{\text{ML}}(N)$ is an MLE based on N iid random variables, with n_θ independent of N , then $\hat{\theta}_{\text{ML}}$ converges to θ_0 almost surely: $\text{a.s.} \lim_{N \rightarrow \infty} \hat{\theta}_{\text{ML}}(N) = \theta_0$.

asymptotic normality: if $\hat{\theta}_{\text{ML}}(N)$ is a MLE based on N iid random variables, with n_θ independent of N , then $\hat{\theta}_{\text{ML}}(N)$ converges in law to a normal random variable with the Cramér-Rao lower bound as covariance matrix.

Bayes estimator: principle

Choose the parameters that have the highest probability:

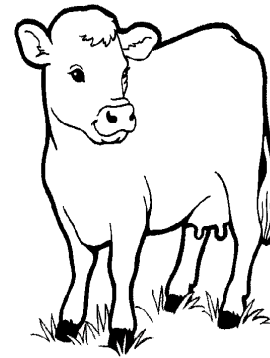
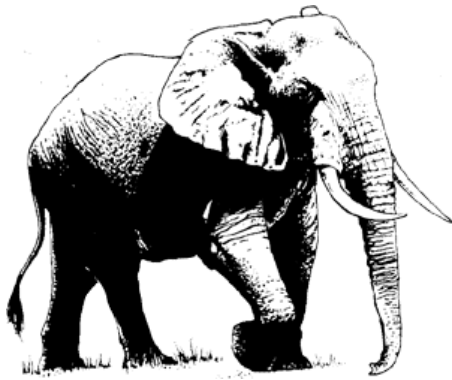
$$\hat{\theta} = \arg \max_{\theta} f(\theta|u, y)$$

Problem: prior distribution of the parameters is required

$$f(\theta|u, y) = \frac{f(y|\theta, u)f(\theta)}{f(y)}$$

Bayes estimator: example 1

Use of Bayes estimators in our daily life



Bayes estimator: example 2

weight of a loaf of bread

Model:

$$y_0 = \theta_0$$

Measurements:

$$y(k) = y_0 + n_y(k)$$

Additional information 1: disturbing noise

The distribution f_y of n_y is $N(0, \sigma_y^2)$

Additional information 2: prior distribution of the parameters

The bread is normally distributed: $N(800\text{gr}, \sigma_w)$

Bayes estimator:

$$f(y|\theta)f(\theta) = \frac{1}{\sqrt{2\pi\sigma_y^2}} e^{-\frac{(y-\theta)^2}{2\sigma_y^2}} \frac{1}{\sqrt{2\pi\sigma_w^2}} e^{-\frac{(\theta-w)^2}{2\sigma_w^2}}$$
$$\hat{\theta} = \frac{z/\sigma_y^2 + w/\sigma_w^2}{1/\sigma_y^2 + 1/\sigma_w^2}$$

Example continued

After making several independent measurements $y(1), \dots, y(N)$

$$f(y|\theta)f(\theta) = \frac{1}{\left(\sqrt{2\pi\sigma_y^2}\right)^N} e^{-\sum_{k=1}^N \frac{(y(k)-\theta)^2}{2\sigma_y^2}} \frac{1}{\sqrt{2\pi\sigma_w^2}} e^{-\frac{(\theta-w)^2}{2\sigma_w^2}}$$

the Bayes estimator becomes

$$\hat{\theta} = \frac{\sum_{k=1}^N y(k)/\sigma_y^2 + w/\sigma_w^2}{N/\sigma_y^2 + 1/\sigma_w^2}$$

For a large number of measurements:

$$\hat{\theta} = \frac{\sum_{k=1}^N y(k)/\sigma_y^2}{N/\sigma_y^2} = \frac{1}{N} \sum_{k=1}^N y(k)$$

Outline

A motivating example: why do *you* need system identification?!

Characterizing estimators

Basic steps of the identification process

A statistic approach to system identification

Identification in the presence of 'input' and 'output' noise

Identification in the presence of input and output noise

Model

$$y_0(k) = g(u_0(k), \theta_0)$$

Measurements

$$u(k) = u_0(k) + n_u(k)$$

$$y(k) = y_0(k) + n_y(k)$$

3 solutions

- MLE formulation --> errors-in-variables EIV
- instrumental variables
- total least squares

Problem

Noise on the regressor --> systematic errors

$$\hat{R}_{LS}(N) = \frac{\frac{1}{N} \sum_{k=1}^N u(k)i(k)}{\frac{1}{N} \sum_{k=1}^N i^2(k)}$$

$$\lim_{N \rightarrow \infty} \hat{R}_{LS}(N) = R_0 \frac{1}{1 + \sigma_i^2 / i_0^2} \quad (0-1)$$

or in general

$$\hat{\theta}_{LS}(N) = (K^T K)^{-1} K^T y$$

quadratic terms --> bias

Errors-in-variables (MLE)

Model

$$y_0(k) = g(u_0(k), \theta_0)$$

Measurements

$$\begin{aligned} u(k) &= u_0(k) + n_u(k) \\ y(k) &= y_0(k) + n_y(k) \end{aligned}, \text{ pdf of the noise}$$

$n_u \rightarrow f_{n_u}$
 $n_y \rightarrow f_{n_y}$

for simplicity: $f(n_u, n_y) = f_{n_u} f_{n_y}$

Cost: likelihood function

$$f((y, u)|(y_0, u_0, \theta_0)) = f_{n_y}(y - y_0|y_0, \theta_0) f_{n_u}(u - u_0|u_0, \theta_0)$$

with

$$y_0(k) = g(u_0(k), \theta_0)$$

Parameters

the model parameters θ_0

the unknown, true input and output: $u_0(k), y_0(k)$

Note that the number of parameters depends on N !!!!!

EIV

Example: Resistance

model

$$u_0(k) = Ri_0(k)$$

measurements

$$u(k) = u_0(k) + n_u(k)$$

$$i(k) = i_0(k) + n_i(k)$$

noise model

$n_u(k), n_i(k)$ i.i.d. zero mean normally distributed

$$n_u(k) \rightarrow N(0, \sigma_u^2)$$

$$n_i(k) \rightarrow N(0, \sigma_i^2)$$

Example EIV (cont'd)

likelihood function

$$f((i, u)|(i_0, u_0, \theta_0)) = f_{n_i}(i - y_0|y_0, \theta_0)f_{n_u}(u - u_0|u_0, \theta_0)$$

with

$$u_0(k) = Ri_0(k)$$

or

$$\frac{1}{(\sqrt{2\pi\sigma_i^2})^N} e^{-\sum_{k=1}^N \frac{(i(k) - i_0(k))^2}{\sigma_i^2}} \quad \frac{1}{(\sqrt{2\pi\sigma_u^2})^N} e^{-\sum_{k=1}^N \frac{(u(k) - u_0(k))^2}{\sigma_u^2}}$$

The cost function becomes

$$V_{\text{MLE}}(i, u, \theta) = \sum_{k=1}^N \frac{(i(k) - i_0(k))^2}{\sigma_i^2} + \frac{(u(k) - u_0(k))^2}{\sigma_u^2}$$

with

$$u_0(k) = Ri_0(k)$$

Example EIV (cont'd)

Elimination of i_0, u_0

$$V_{\text{MLE}}(i, u, \theta) = \sum_{k=1}^N \frac{(Ri(k) - u(k))^2}{\sigma_u^2 + R\sigma_i^2}$$

Solution

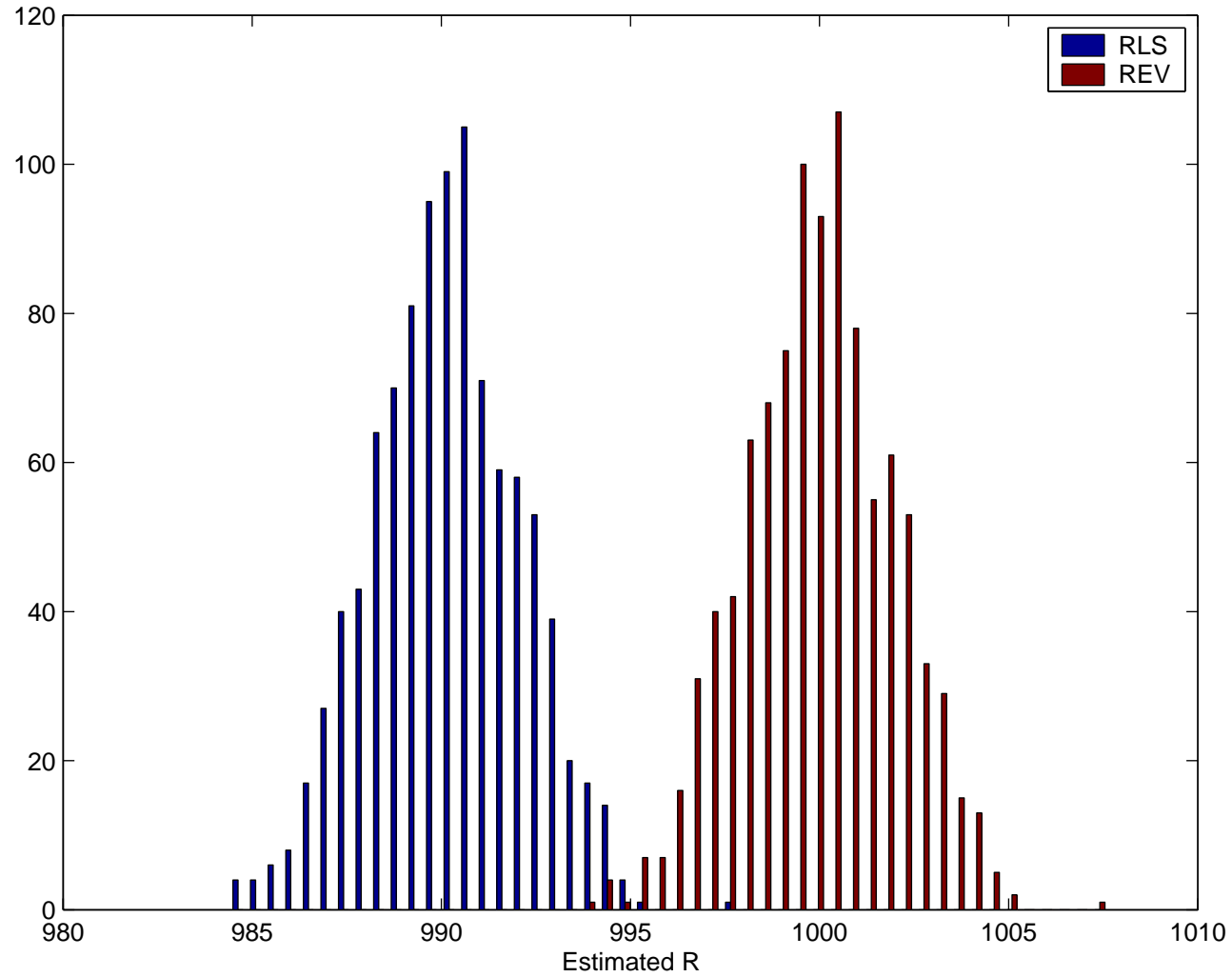
$$\hat{R}_{\text{EIV}} = \frac{\frac{\sum u(k)^2}{\sigma_u^2} - \frac{\sum i(k)^2}{\sigma_i^2} + \sqrt{\left(\frac{\sum u(k)^2}{\sigma_u^2} - \frac{\sum i(k)^2}{\sigma_i^2}\right)^2 + 4 \frac{(\sum u(k)i(k))^2}{\sigma_u^2 \sigma_i^2}}}{\frac{\sum u(k)i(k)}{\sigma_u^2}},$$

compare to the Least Squares estimator

$$\hat{R}_{\text{LS}} = \frac{\sum_{k=1}^N u(k)i(k)}{\sum_{k=1}^N i(k)^2}$$

Example: Resistance

$$R_0 = 1000, i_0: N(0, 0.01^2), \sigma_i^2 = 0.001^2, \sigma_u^2 = 1$$



Outline

A motivating example: why do *you* need system identification?!

Characterizing estimators

Basic steps of the identification process

A statistic approach to system identification

Identification in the presence of 'input' and 'output' noise

Next lesson

Frequency Response Function Measurements (February 8)

Impact of Nonlinear Distortions on the Linear Framework (February 15)

System Identification (February 22)

Identification of Linear Systems (March 1)

Identification of Nonlinear Systems (March 8)