

Estimating errors in clinical MRS

D. van Ormondt, Applied Physics, TU Delft, NL



Transforming Magnetic Resonance Spectroscopy into a Clinical Tool



2nd Transact Workshop

16/18-06-2014, Bern University Hospital, CH

**Quality issues in clinical
MR Spectroscopy**

CONTENTS

Item	Slides
Title	1
Contents	1
Rationale of error estimation	1
Error estimation by Monte-Carlo simulation	3
Alternative error estimation needed for Clinics	1
Practical alternative error: Cramér-Rao Bound	3
Result of Monte-Carlo- & Cramér-Rao-estimations	3
Residue of model-fitting	1
Summary & Recommendation	1
Supplement	4
Acknowledgement	1
Appendix	1
Total	21

Needed: Awareness of how to estimate errors

Metabolite concentrations to be estimated in vivo.



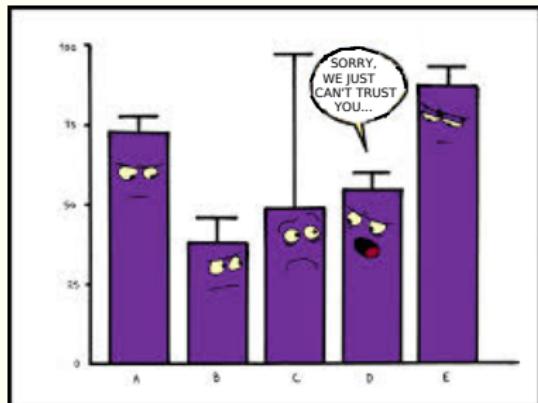
Error bars on concentrations must be reliable: Not trivial.

MRS uses CRB

$$\text{CRB} = \frac{\sigma^2}{a, \sigma^2} (\zeta_1) = \frac{\zeta_1 - \mu}{\sigma^2} f_{a, \sigma^2}(\xi_1) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(\zeta_1 - \mu)^2}{2\sigma^2}\right)$$

$$\int T(x) \cdot \frac{\partial}{\partial \theta} f(x, \theta) dx = M(T(\xi)) \cdot \frac{\partial}{\partial \theta} \ln L(\xi, \theta) \int \frac{\partial}{\partial \theta} \ln L(x, \theta) dx$$

$$f_{a, \sigma^2}(\zeta_1) \cdot \left(\frac{\partial}{\partial \theta} \ln L(x, \theta) \right) \cdot f(x, \theta) dx = \int T(x) \cdot \frac{\partial}{\partial \theta} \ln L(x, \theta) dx$$



MONTE-CARLO SIMULATION: HOW TO DO I

From 10 metabolites
with signals/spectra

S_1, \dots, S_{10} ,

and concentrations

C_1, \dots, C_{10} ,

make a signal S .

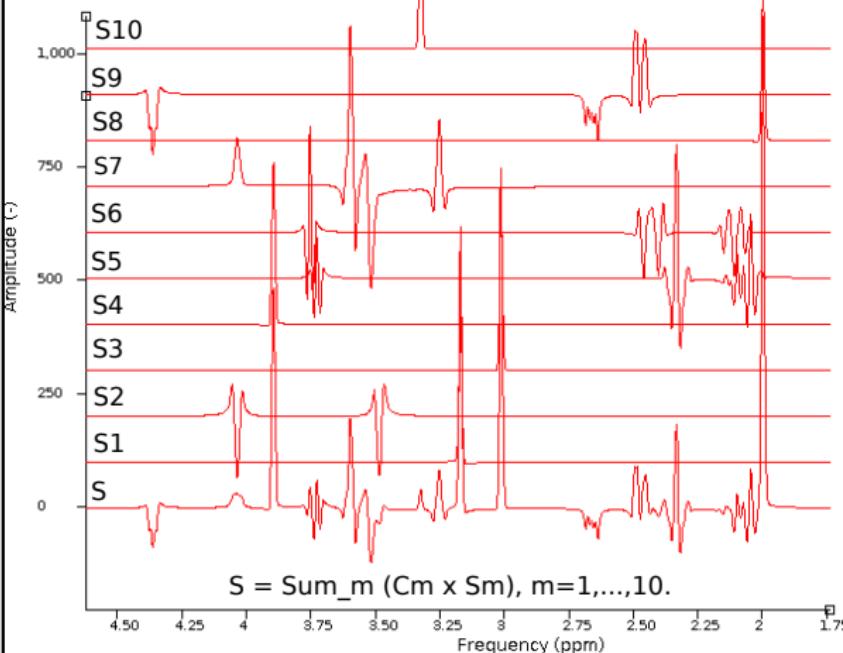
Make 100 noisy
versions of S . p5

For each version,
estimate C_1, \dots, C_{10}
with, e.g., QUEST,
approximating the
form of the decay of
 S with, e.g., e^{at} .

11.7 T. Signal database by R. de Beer.

$$\begin{aligned} C_1 &= 1.755, C_2 = 0.192, C_3 = 2.067, C_4 = 1.357, C_5 = 0.633 \\ C_6 &= 0.147, C_7 = 0.553, C_8 = 2.974, C_9 = 0.661, C_{10} = 0.120 \end{aligned}$$

S is made to decay non-exponentially



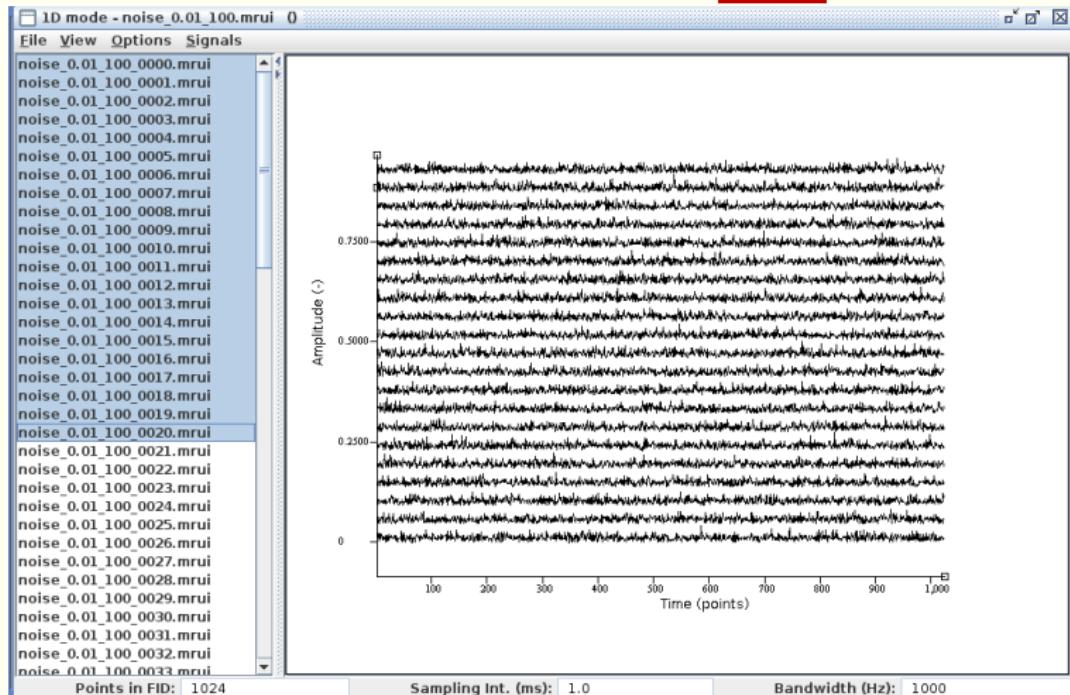
The 100 sets of estimated C_1, \dots, C_{10} yield distribution of errors.

Reminder: spectrum = FFT[signal].

MONTE-CARLO SIMULATION: HOW TO DO II

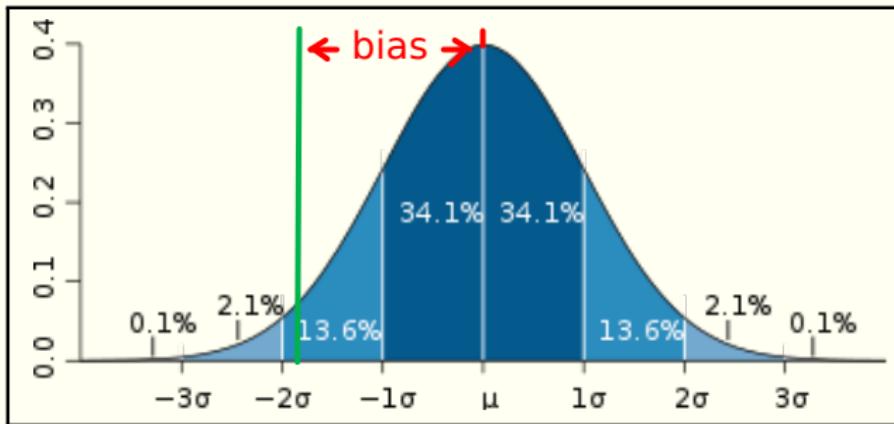
Noise realisations

jMRUI
TRANSPORT



Each **noise-realisation** has equal stdev, σ , and mean, μ ($= 0$).

MONTE-CARLO SIMULATION: RESULT



Distribution of estimated values of a parameter.

- ▶ A Monte-Carlo simulation yields σ, μ, bias for each estimated (= fitted) parameter. 😊
- ▶ Bias ($= \mu - \text{true value}$) is caused by, e.g., *incorrectness* of a model function, or *sub-optimality* of the used parameter-estimator. [gotoslide4](#)
- ▶ 🤝 In simulations, the **true values** are, of course, known. Not so in the clinic.

MONTE-CARLO: USEFUL IN THE CLINIC?

- 👉 In clinics, only a single measurement is available.
- 👉 Monte-Carlo simulations are less of an option.



**ALTERNATIVE NEEDED
IN CLINICAL ROUTINE:**
Harald Cramér
Radhakrishna Rao

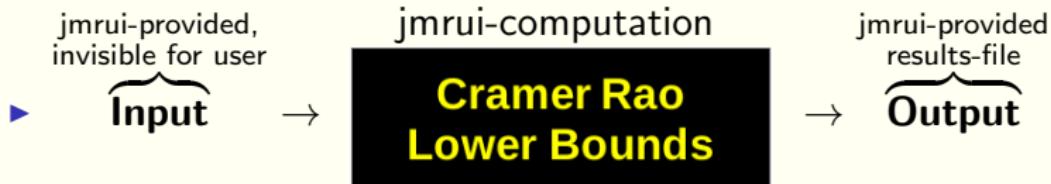


MRS uses pragmatic error-estimation (JMR, 1986)
CRB – Cramér-Rao (lower) Bound –

Contained in jMRUI, LCModel, etc.

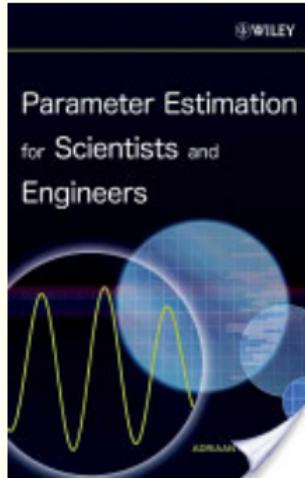
CRB I. Theory & Computation

- ▶ CRB considered as 'black box' with input and output



- ▶ Info on Theory & Computation

A. van den Bos :



D. Graveron-Demilly :
Quantification in magnetic resonance spectroscopy based on semi-parametric approaches.
Magn Reson Mater Phy 27:113-130, 2014,
and references therein.

Google

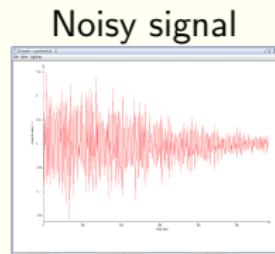
CRB II. Input for CRB-computation. Exact vs In Vivo.

1. Exact model function of the MRS-signal,

in vivo \rightarrow problematic

$$\text{e.g.: } s(t) = \overbrace{\text{decay}(t)}^? \times \sum_{m=1}^{10} c_m s_m(t).$$

- ▶ *In vivo:* $\text{decay}(t) \stackrel{?}{\approx} \underbrace{e^{\alpha t}, e^{\beta t^2}, e^{\alpha t + \beta t^2}}_{\text{surrogate model}}$, etc.



2. Exact concentrations, decay-parameters .

- ▶ *In vivo:* parameters estimated.

3. Exact pdf of the noise.

- ▶ *In vivo:* Consensus: Gaussian pdf assumed.
- ▶ *In vivo:* σ, μ estimated.

Gaussian pdf

$$f(x; \mu, \sigma) = \frac{e^{-(x-\mu)^2/2\sigma^2}}{\sqrt{2\pi\sigma^2}},$$

with

$x = \text{noise}.$

N.B. $\text{CRB} \propto \sigma.$

Individual values $\sigma(t)$ of the actual noise realisation do NOT enter the CRB computation (estimation).

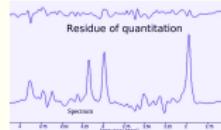
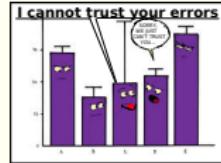
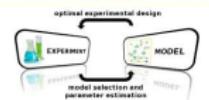
CRB III. Output of CRB-computation

- ▶ Standard deviation of each estimated parameter.
- ▶ Correlations between estimated parameters.

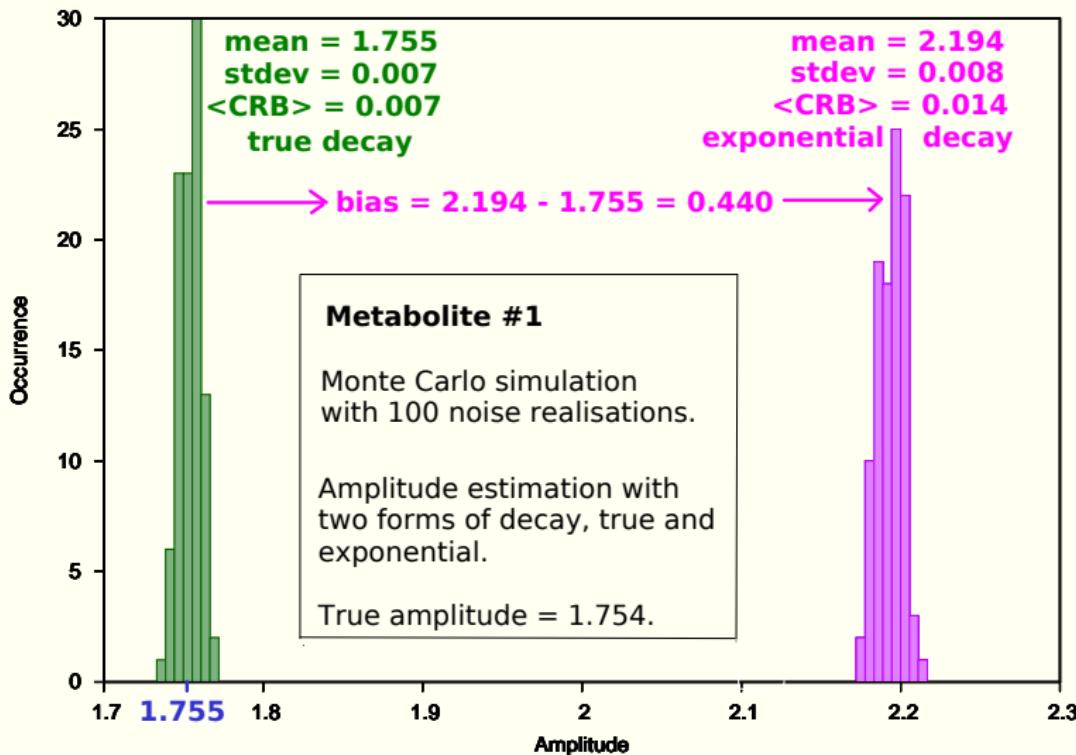


Remarks

- ▶ Parametric case: Model function **correct** and **complete**. No Bias. Application of CRB warranted and highly recommended.
- ▶ CRB's and correlations are useful for experimental design and cost estimation.
- ▶ Semi-parametric case: Model function supplemented with 'surrogate' model function. Bias incurred, unknowingly.
CRB may lead clinicians & others astray.
- ▶ How to judge semiparametric model function? From residue? Statistics package 'R'?



Results: Monte-Carlo simulation I



gotoslide4

Mean and stdev of Monte-Carlo simulation versus CRB.

Table: Results for true form of the decay, i.e., parametric case .

m	$\mu_{c_m}^{\dagger}$	c_m^{true}	bias_{c_m}	$\sigma_{c_m}^{\ddagger}$	$\mu_{\text{CRB}_{c_m}}^{\dagger}$
1	1.7541	1.7550	-0.0008	0.0069	0.0071
2	0.1923	0.1921	0.0002	0.0081	0.0093
3	2.0665	2.0673	-0.0008	0.0073	0.0074
4	1.3582	1.3563	0.0019	0.0067	0.0070
5	0.6330	0.6330	-0.0000	0.0055	0.0059
6	0.1472	0.1472	-0.0000	0.0072	0.0069
7	0.5523	0.5527	-0.0004	0.0036	0.0042
8	2.9743	2.9742	0.0001	0.0084	0.0083
9	0.6611	0.6609	0.0003	0.0062	0.0069
10	0.1208	0.1199	0.0009	0.0060	0.0063

\dagger) μ stands for mean, \ddagger) σ stands for standard deviation.

Mean and stdev of Monte-Carlo simulation versus CRB.

Results: Monte-Carlo simulation III

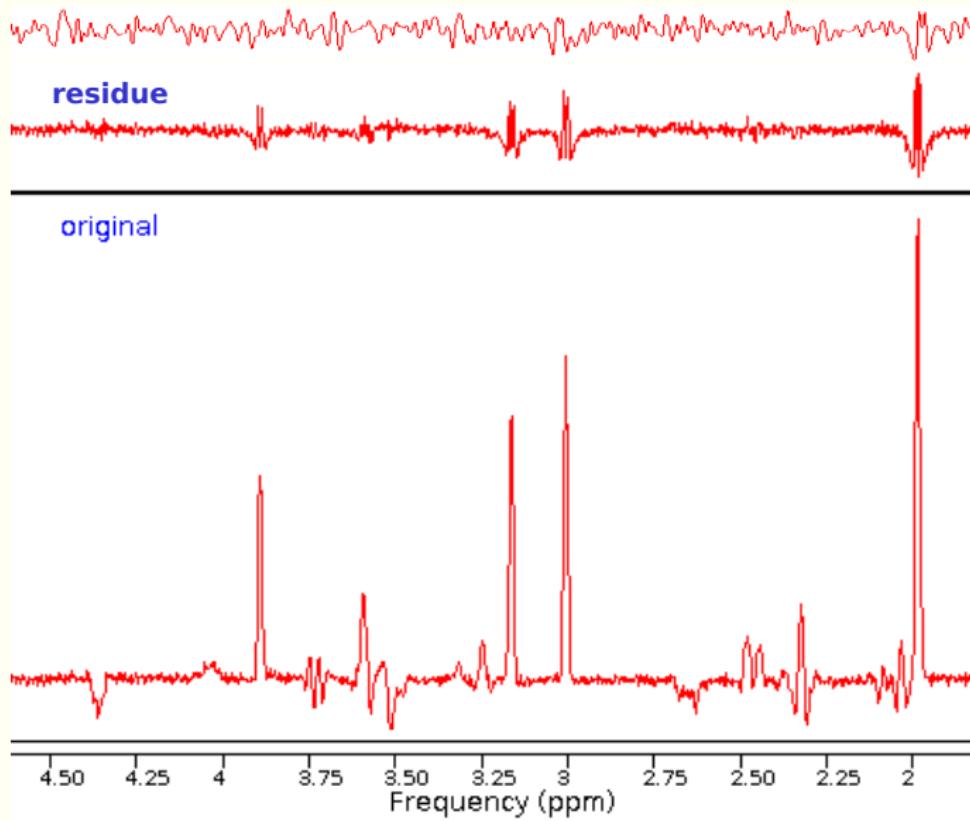
Table: Results for exponential decay, i.e., semi-parametric case.

m	$\mu_{c_m} \dagger$	c_m^{true}	bias_{c_m}	$\sigma_{c_m} \ddagger$	$\mu_{\text{CRB}_{cm}} \dagger$	$\sigma_{\text{CRB}_{cm}} \ddagger$
1	2.1937	1.7550	0.4387	0.0080	0.0143	0.00009
2	0.2288	0.1921	0.0367	0.0111	0.0217	0.00014
3	2.5850	2.0673	0.5176	0.0079	0.0143	0.00010
4	1.6943	1.3563	0.3380	0.0078	0.0139	0.00009
5	0.8960	0.6330	0.2630	0.0074	0.0137	0.00009
6	0.1980	0.1472	0.0508	0.0097	0.0156	0.00011
7	0.7104	0.5527	0.1577	0.0046	0.0091	0.00006
8	3.7260	2.9742	0.7517	0.0088	0.0160	0.00010
9	0.7762	0.6609	0.1153	0.0075	0.0136	0.00009
10	0.1446	0.1199	0.0247	0.0076	0.0133	0.00009

\dagger) μ stands for mean, \ddagger) σ stands for standard deviation.

Mean and stdev of Monte-Carlo simulation versus CRB.

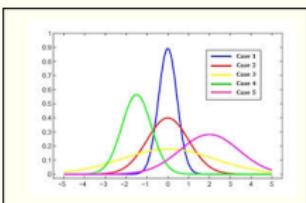
Residue of the quantitation



SUMMARY

- ▶ Cramér-Rao :
 - ▶ Parametric case: Ideal. 
 - ▶ Semi-parametric case: Bias.
CRB too low.

- ▶ Monte-Carlo :
 - ▶ Provides crucial insight, especially in semi-parametric estimation.
 - ▶ Simulation of 'real-world' signals may be difficult.
 - ▶ Not applicable in clinical routine.

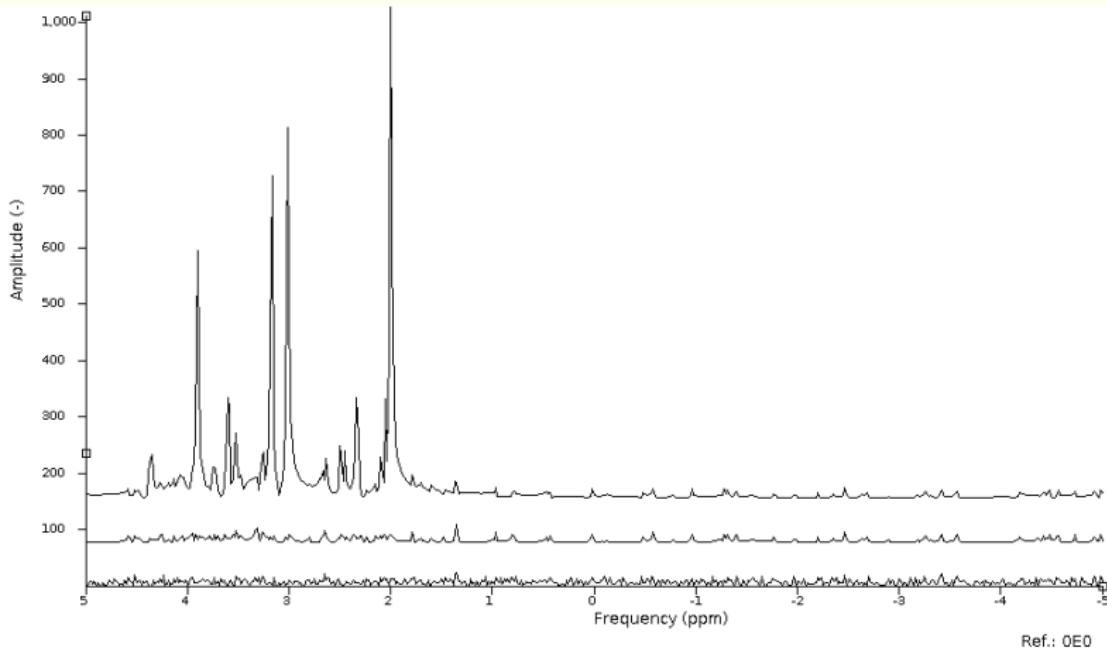


RECOMMENDATIONS

- ☞ Dramatic increase of SNR: 'hp', etc.
- ☞ Spectral editing.
- ☞ Denoising ?



DENOISING, 'SVD-truncation' I



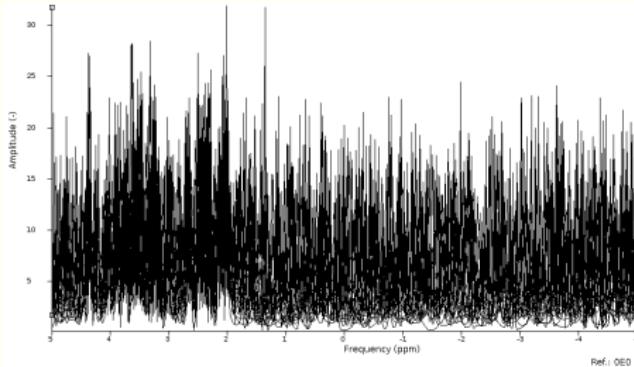
Single noise realisation shown. Absolute values.

Upper: FFT of denoised signal, 11.7 T.

Middle: FFT of denoised signal minus noiseless, true signal.

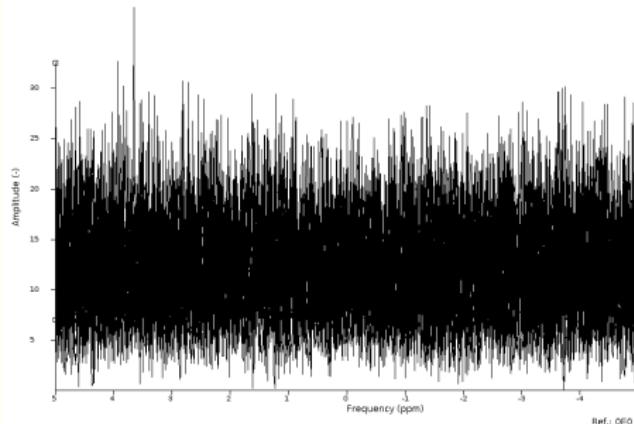
Lower: FFT of original noise.

DENOISING, 'SVD-truncation' II



Superimposed FFTs of 20 denoised signals from which the true, noiseless signal has been subtracted, i.e., only noise and signal deformation remain.
Absolute values.

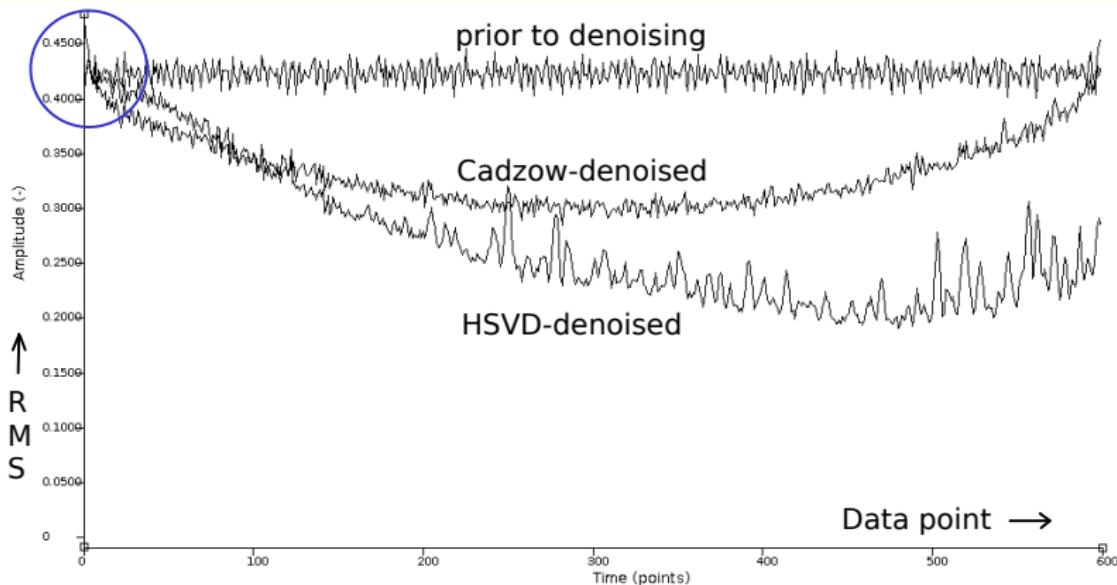
pdf of noise perturbed ↑



Superimposed FFTs of the 20 corresponding original noise realisations.
Absolute values.

DENOISING, 'SVD-truncation' III. Time domain.

$$\text{RMS}[\|s_{\text{not-/post-denoised}} - s_{\text{true_noiseless}}\|]$$



For each data point: RMS of noise in original noisy signal
and in two denoised versions, using 10^3 noise realisations.
MRS model function not used. RMS = root-mean-square.

DENOISING IV. Remarks

- ▶ Denoising of signals is indeed observed,
 - ▶ in both time-domain and frequency-domain.
 - ▶ Useful for, e.g., MRI (non-parametric).
 - ▶ Denoising of metabolite resonances?
 - ▶ Metabolite quantitation benefits?
- ▶ Parametric metabolite quantitation with jMRUI, LCModel, etc., already amounts to optimal denoising, because :
 - ▶ Parametric estimation errors, obtained with the un-denoised signal, reach the CRLowerB. Hence : 
 - ▶ Reconstruction of the signal from the estimated model parameters yields optimal denoising.
- ▶ statusquo@dvo :
Using Monte-Carlo simulations, reduction of error bars of metabolite quantitation **not** found, so far.

ACKNOWLEDGEMENT

**TRANSACT is made possible by the EUROPEAN UNION
and its common currency, the EURO.**



Delors



Euro coins



Draghi

**“UNITED WE STAND, DIVIDED WE FALL”
In 26 centuries old fable : The Four Oxen and the Lion.**



Two alternative definitions of ‘estimation’

awareness

www.merriam-webster.com/dictionary/estimation :

1. Guess  about size, amount, cost, ... , of something.
☞ Not meant here.
2. Use of a function or formula — ‘estimator’ — to derive a solution or make a prediction. Unlike guess, it has precise connotations.

