Correlation analysis for long time series by robustly estimated autoregressive stochastic porcesses

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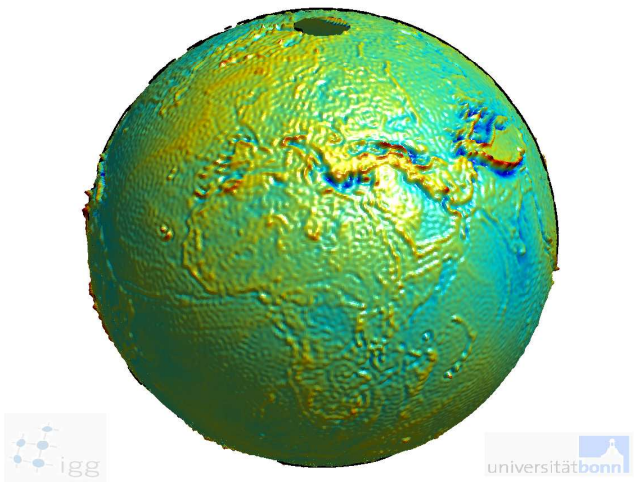
Motivation

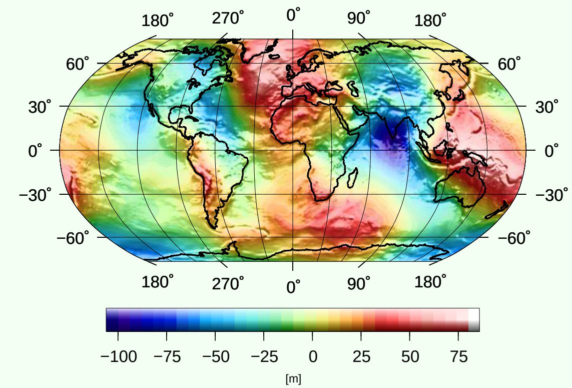


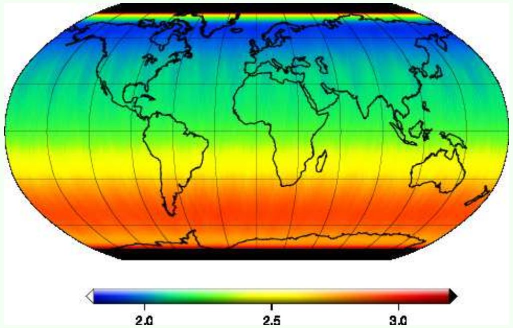
G O C E gravity field

geoid heights:	±100 m
accuracy:	±2.8 cm
	±0.8 mgal
resolution:	100 km
	d/o 200

homogeneous global precision

gravity field model
(78.400 parameter)

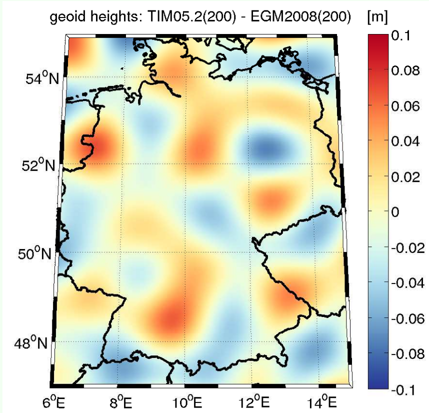




formal accuracy
(±2.0-3.0 cm)

external validation

TIM05-EG2008: Germany
(rms: ±2.7 cm)



- **consistent modeling of the error budget**
- **variance/covariance information available**

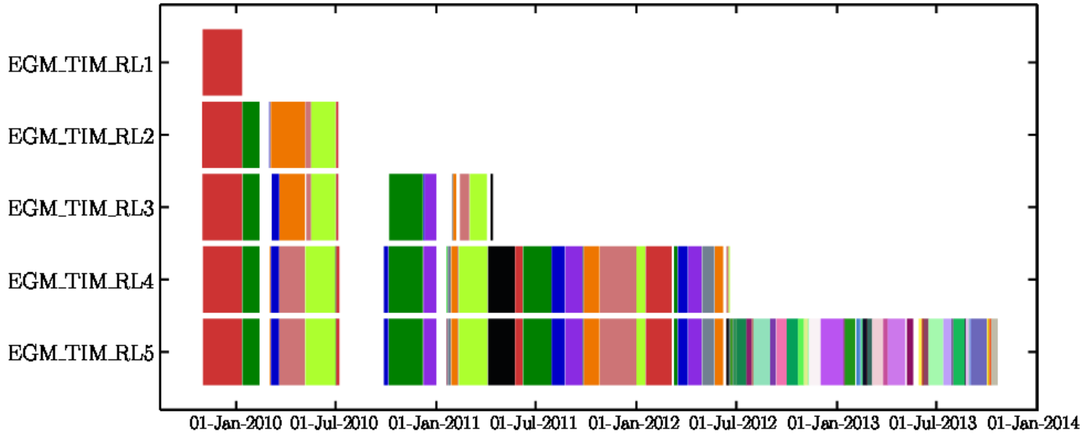
Brockmann et.al. (2014): EGMTIMRL05: An Independent Geoid with Centimeter Accuracy Purely Based on the GOCE Mission. *Geophysical Research Letters* 41(22), 8089-8099

GOCE - data characteristics

- huge number of measurements
- time variable behavior
- strongly correlated measurement noise
- conspicuous data especially
  in the low orbit operation campaign

GOCE-TIM data segments

440 mio observations, eff. 1273 days, 88 segments



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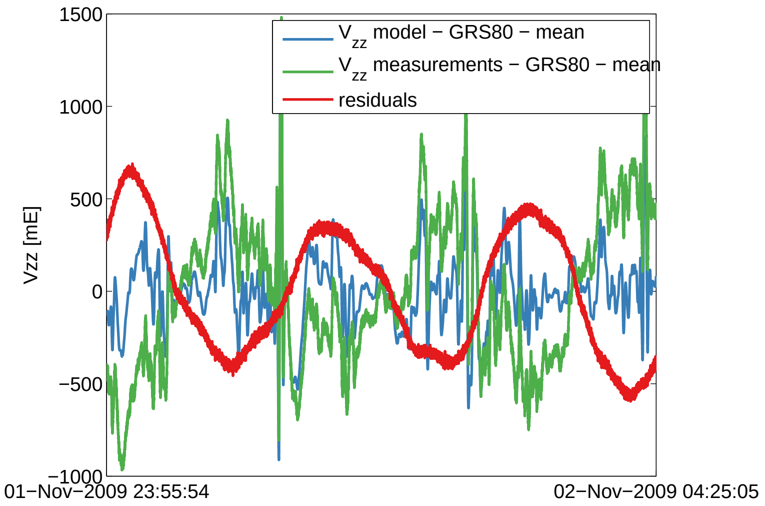
signal vs. noise



GOCE-TIM data segments

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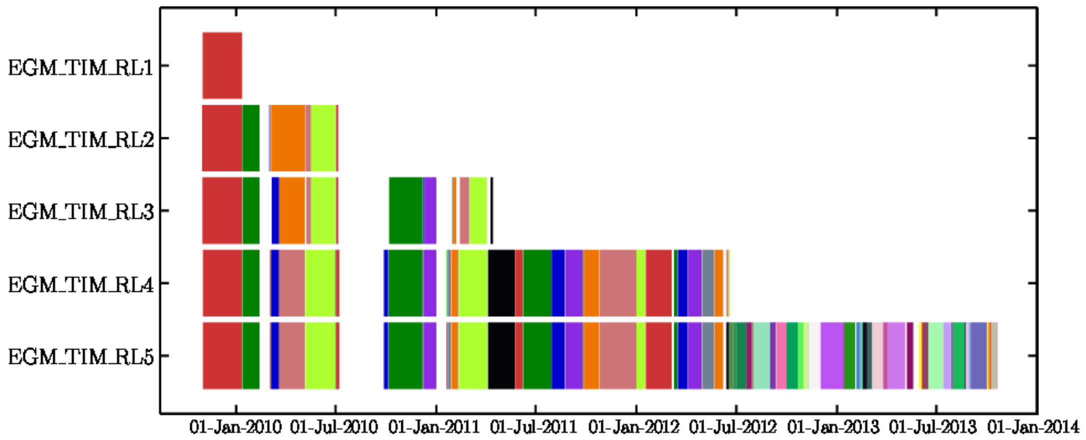

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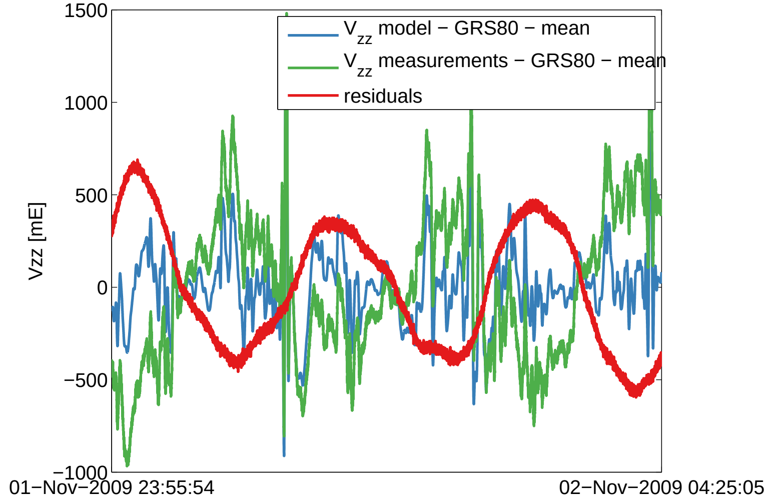
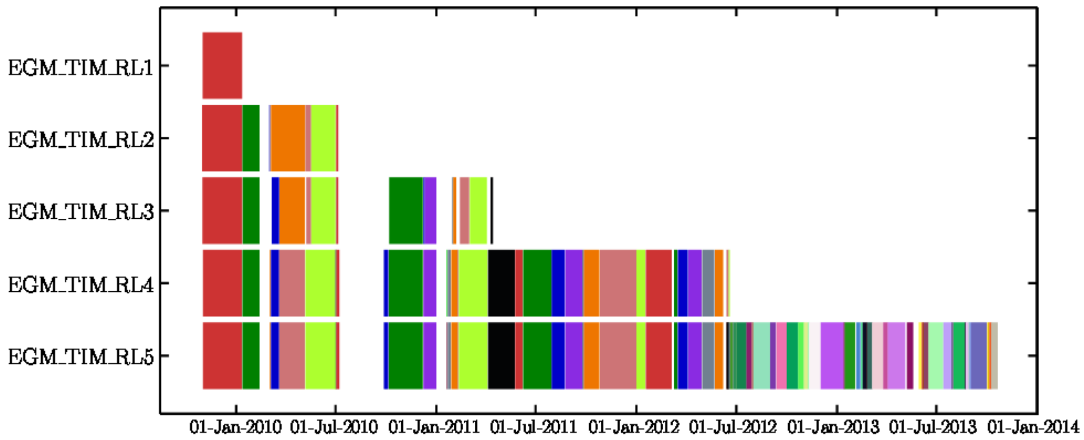
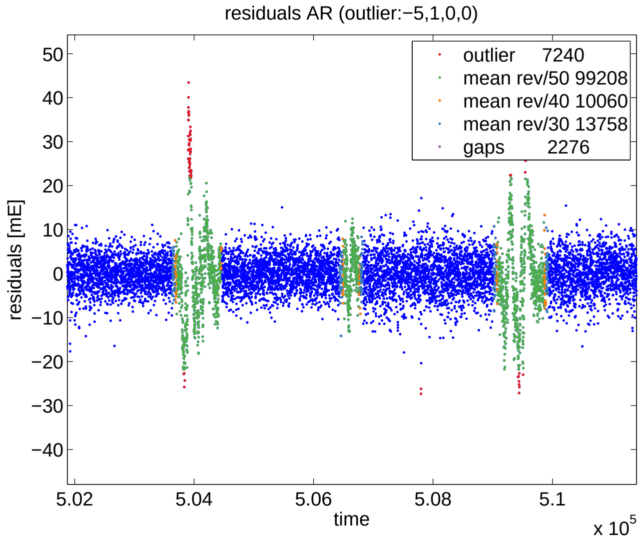


GOCE-TIM data segments

440 mio observations, eff. 1273 days, 88 segments



conspicuous data



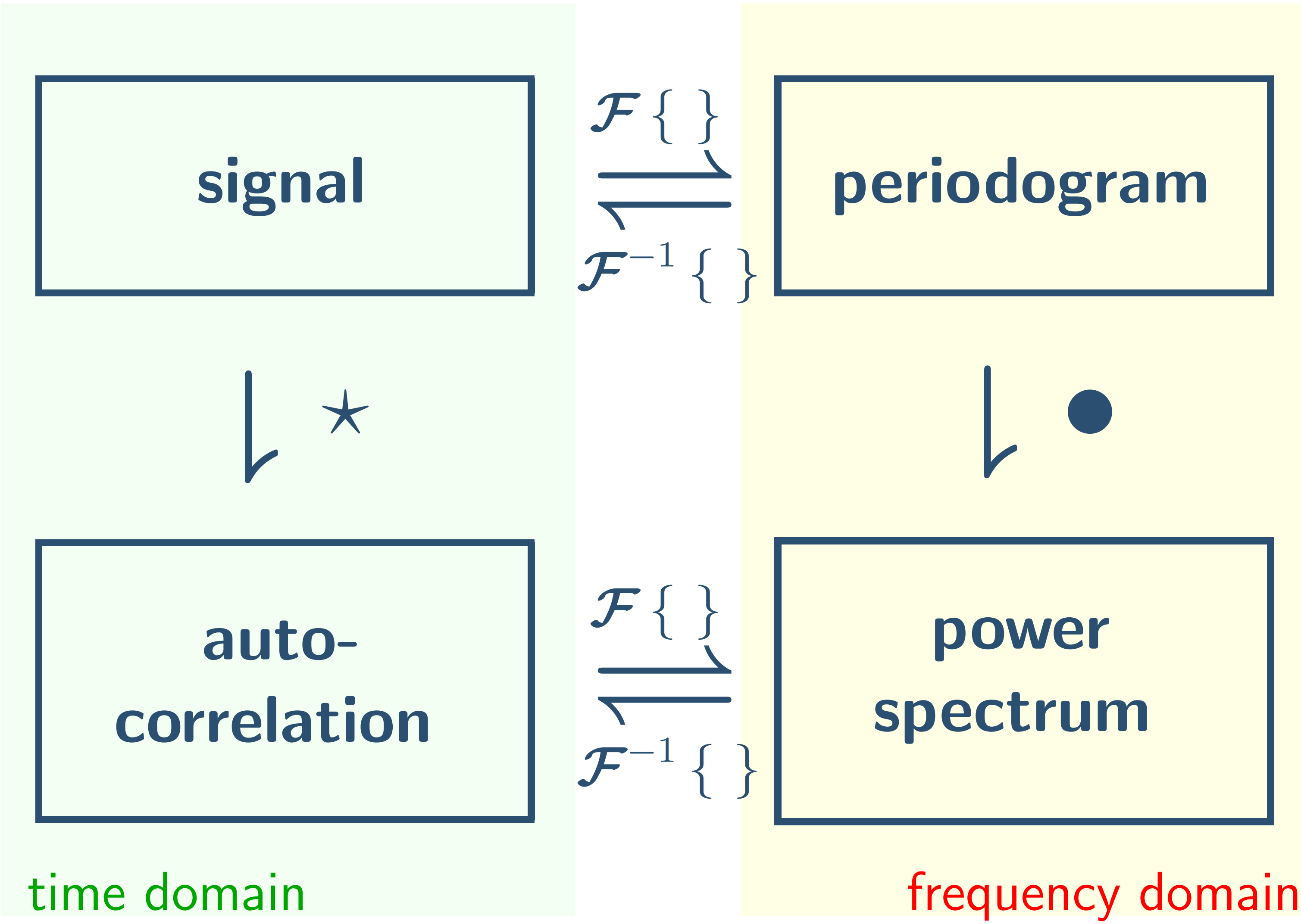
Goals

Goals of this presentation:

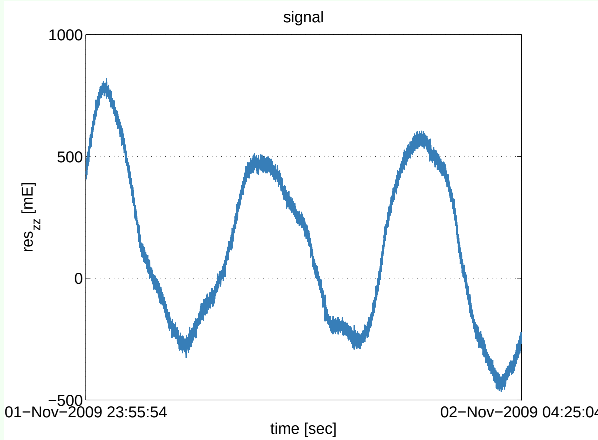
- Approach for an optimal description of the stochastic behavior of GOCE data
- Identification of conspicuous data
- Demonstration of first results with real GOCE data

Magic Square - Spectral Estimation

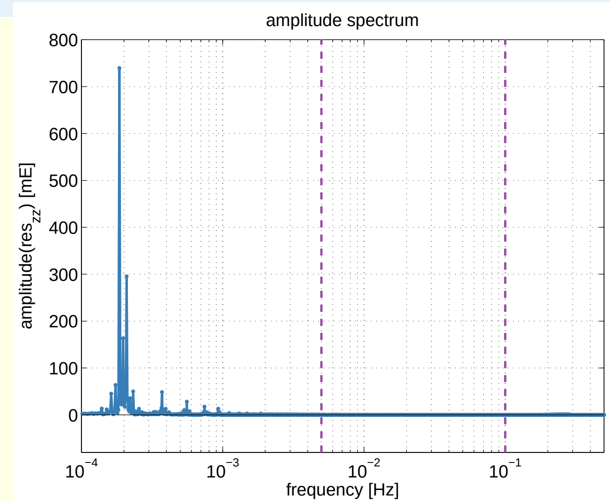
Magic Square



Representation of GOCE noise in different states



$\mathcal{F}\{\ \}$



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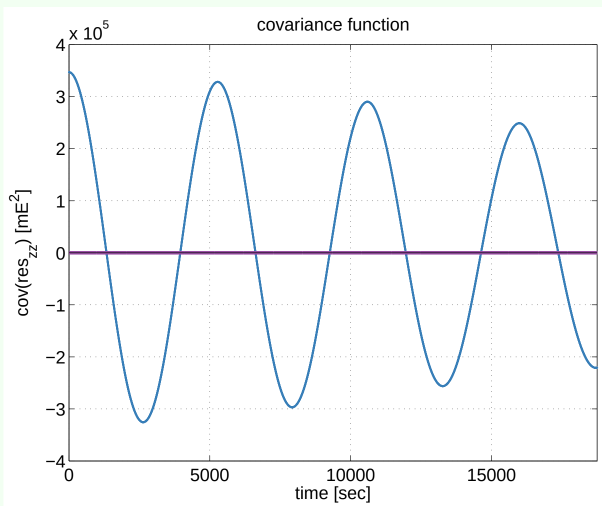

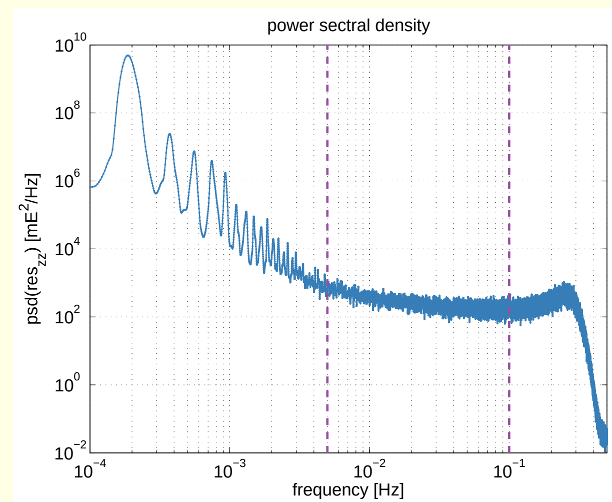

time domain

frequency domain

Magic Square - stationary stochastic signal

time domain		frequency domain
stochastic signal	$\underset{\mathcal{F}^{-1}\{\ \}}{\overset{\mathcal{F}\{\ \}}{\rightleftharpoons}}$	**???**
$\upharpoonleft\downharpoonright\ \star$		$\upharpoonleft\downharpoonright\ \bullet$
???	$\underset{\mathcal{F}^{-1}\{\ \}}{\overset{\mathcal{F}\{\ \}}{\rightleftharpoons}}$	**???**

Magic Square - stationary stochastic signal

time domain		frequency domain
stochastic signal $\mathcal{S}(t)$	$\mathcal{F}\{\ \}$ $\rightleftharpoons$ $\mathcal{F}^{-1}\{\ \}$	**orthogonal stoch. signal** $\mathcal{Z}(\nu)$
$\downarrow E\{(\mathcal{S}(t)-\mu)(\mathcal{S}(t+k)-\mu)\}$		$\downarrow E\{\mathcal{Z}(\nu)\bullet\mathcal{Z}(\nu)^*\}$
auto-covariances $\gamma(k)$	$\mathcal{F}\{\ \}$ $\rightleftharpoons$ $\mathcal{F}^{-1}\{\ \}$	**distribution function** $F(\nu)$

Magic Square - stationary stochastic signal

$$\{\mathcal{S}_k\}_{\Delta t}$$

$$d\mathcal{Z}(\nu) = \Delta t \sum_{k=-\infty}^{\infty} \mathcal{S}_k \int_{\nu}^{\nu+\Delta\nu} e^{-i2\pi\nu k\Delta t}\, d\nu$$

$$\rightleftharpoons$$

$$\mathcal{S}_k = \int_{-\nu^N}^{\nu^N} e^{i2\pi\nu k\Delta t}\, d\mathcal{Z}(\nu)$$

$$d\mathcal{Z}(\nu)\Big|_{-\nu^N}^{\nu^N}$$

$$E\left\{(\mathcal{S}_u-\mu)(\mathcal{S}_{u+k}-\mu)\right\} \downarrow$$

$$\frac{1}{\Delta t} E\left\{d\mathcal{Z}(\nu)\bullet d\mathcal{Z}(\nu)^*\right\} \downarrow$$

$$\{\gamma_k\}$$

$$dF(\nu) = \Delta t \sum_{k=-\infty}^{\infty} \gamma_k \int_{\nu}^{\nu+\Delta\nu} \cos(2\pi\nu k\Delta t)\, d\nu$$

$$\rightleftharpoons$$

$$\gamma_k = \int_{-\nu^N}^{\nu^N} \cos(2\pi\nu k\Delta t)\, dF(\nu)$$

$$dF(\nu)\Big|_{-\nu^N}^{\nu^N}$$

time domain

frequency domain

Krasbutter et.al (2015): Magic Square of Real Spectral and Time Series Analysis with an Application to Moving Average Processes. *IAG Symposia* 140, 9-14, Springer

$$\boxed{\{\mathcal{S}_k\}_{\Delta t}}$$

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$$\boxed{dF(\nu)\Big|_{-\nu^N}^{\nu^N}}$$

time domain

frequency domain

covariance stationary discrete equispaced stochastic signal

Kay/Marple (1981): Spectrum Analysis - A Modern Perspective. *Proceedings of the IEEE* 69(11), 1380-1419

non-parametric spectral estimation

$$d\mathcal{Z}(\nu) = \Delta t \sum_{k=-\infty}^{\infty} \mathcal{S}_k \int_{\nu}^{\nu+\Delta\nu} e^{-i2\pi\nu k\Delta t} d\nu$$

$$\boxed{\{\mathcal{S}_k\}_{\Delta t}} \rightleftharpoons \boxed{d\mathcal{Z}(\nu)\Big|_{-\nu^N}^{\nu^N}}$$

$$\mathcal{S}_k = \int_{-\nu^N}^{\nu^N} e^{i2\pi\nu k\Delta t} d\mathcal{Z}(\nu)$$

$$E\{(\mathcal{S}_u - \mu)(\mathcal{S}_{u+k} - \mu)\}$$

$$\frac{1}{\Delta t} E\{d\mathcal{Z}(\nu) \bullet d\mathcal{Z}(\nu)^*\}$$

$$\int_{\nu}^{\nu+\Delta\nu} \cos(2\pi\nu k\Delta t) d\nu$$

Blackman-Tukey approach

$$\boxed{\{\gamma_k\}} \rightleftharpoons \boxed{dF(\nu)\Big|_{-\nu^N}^{\nu^N}}$$

$$\gamma_k = \int_{-\nu^N}^{\nu^N} \cos(2\pi\nu k\Delta t) dF(\nu)$$

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$\{\mathcal{S}_k\}_{\Delta t}$

$d\mathcal{Z}(\nu)\Big|_{-\nu^N}^{\nu^N}$

averaging periodogram (Welch) approach

$E\{(\mathcal{S}_u - \mu)(\mathcal{S}_{u+k} - \mu)\}$

$\frac{1}{\Delta t} E\{d\mathcal{Z}(\nu) \bullet d\mathcal{Z}(\nu)^*\}$

$\int^{\nu+\Delta\nu} \cos(2\pi\nu k\Delta t) d\nu$

$\{\gamma_k\}$

Blackman-Tukey approach

$dF(\nu)\Big|_{-\nu^N}^{\nu^N}$

$$\gamma_k = \int_{-\nu^N} \cos(2\pi\nu k\Delta t) dF(\nu)$$

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$$E\{(\mathcal{S}_u - \mu)(\mathcal{S}_{u+k} - \mu)\}$$

smoothed periodogram approach

Blackman-Tukey approach

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time domain

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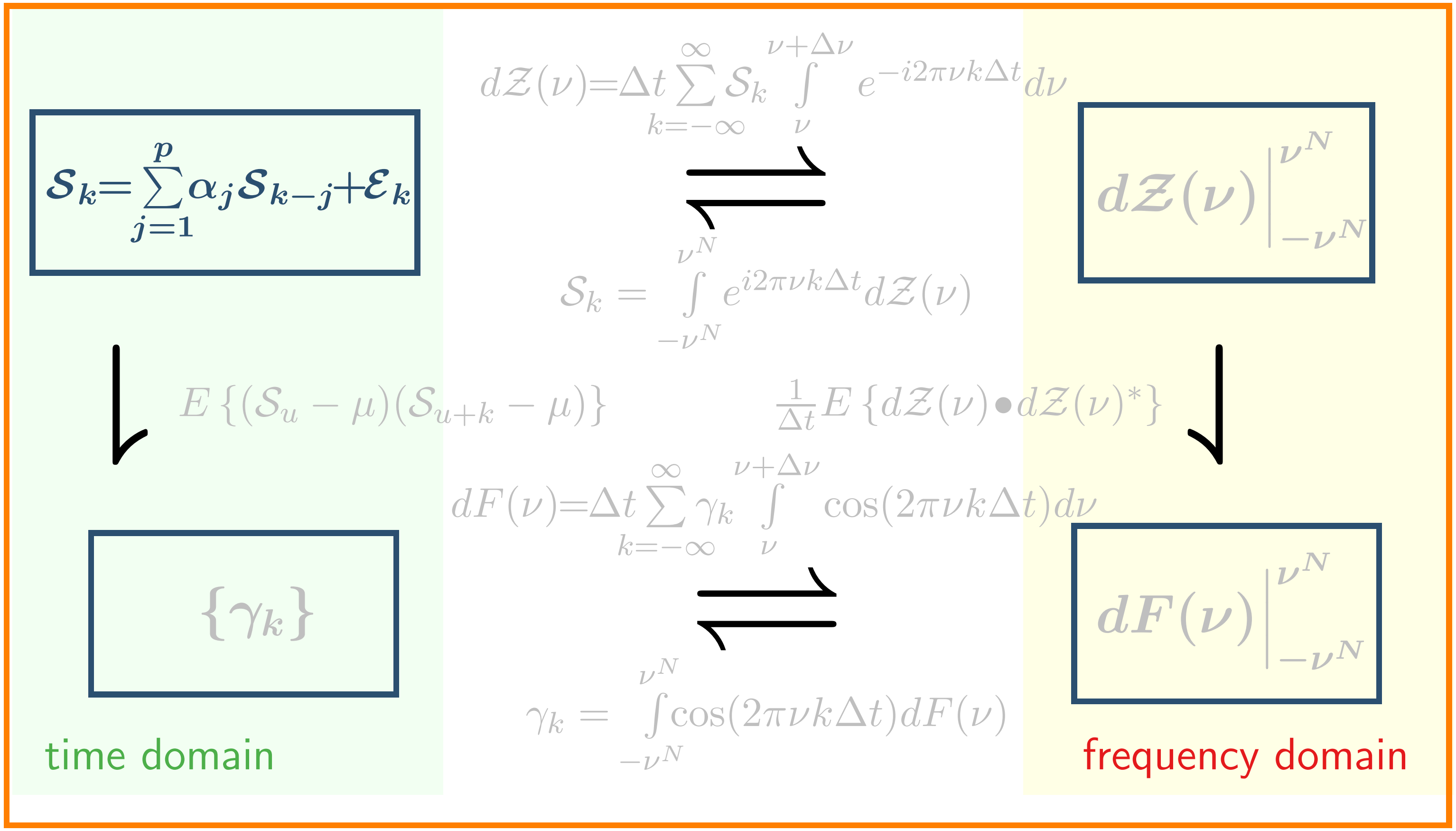
parametric spectral estimation

parametric spectral estimation



AR(p)-auto-regressive process (equivalent to MA or ARMA representation — Wold (1938)

Wold (1938): A study in the analysis of stationary time series. *Almqvist & Wiksell*

parametric spectral estimation

$$\mathcal{S}_k = \sum_{j=1}^{p} \alpha_j \mathcal{S}_{k-j} + \mathcal{E}_k$$

$\mathcal{F}\{\ \}$

$$d\mathcal{Z}_{\mathcal{S}}(\nu) = \frac{d\mathcal{Z}_{\mathcal{E}}(\nu)}{1-\sum_{j=1}^{p} \alpha_j e^{-i2\pi\nu j\Delta t}}\Bigg|_{-\nu^N}^{\nu^N}$$

Yule-Walker equation

$$E\left\{\frac{1}{\Delta t} d\mathcal{Z}_{\mathcal{S}}(\nu) \bullet d\mathcal{Z}_{\mathcal{S}}(\nu)^*\right\}$$

$$\{\gamma_k\}$$

$$\{\gamma_k\} * \{\bar{\alpha}_k\} = -\{\delta_0\}\,\sigma_{\mathcal{E}}^2$$

$$f_{\mathcal{S}}(\nu) = \Delta t \sigma_{\mathcal{E}}^2 \Big/ \Big(1 + \alpha_p^2 - 2\alpha_p \cos(2\pi\nu p\Delta t) + \sum_{j=1}^{p-1} \Big(\alpha_j^2 - 2\cos(2\pi\nu j\Delta t)\big(\alpha_j - \sum_{k=1}^{p-j} \alpha_k \alpha_{k+j}\big)\Big)\Big)\Bigg|_{-\nu^N}^{\nu^N}$$

time domain

frequency domain

AR(p)-auto-regressive process — Magic Square

Schuh et.al. (2014): Korrelierte Messung - was nun? In: Neuner (Ed): *Zeitabhängige Messgrößen - Ihre Daten haben (Mehr-)Wert*, Wißner, Augsburg, 74, 85 - 101

parametric spectral estimation

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Yule-Walker approach

$\{\delta_0\}\ \sigma_{\mathcal{E}}^2$

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time domain

frequency domain

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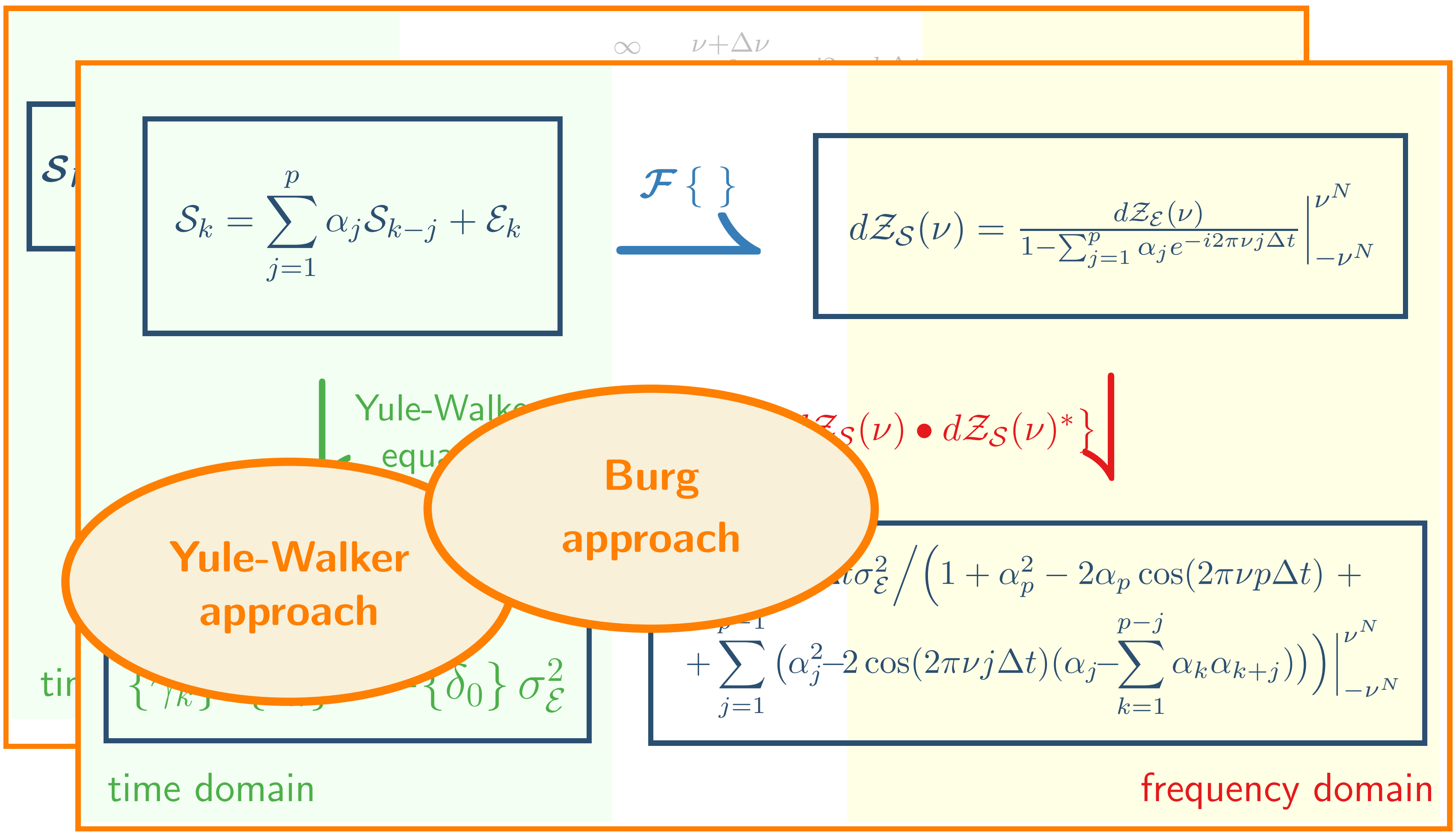
parametric spectral estimation



AR(p)-auto-regressive process — Magic Square

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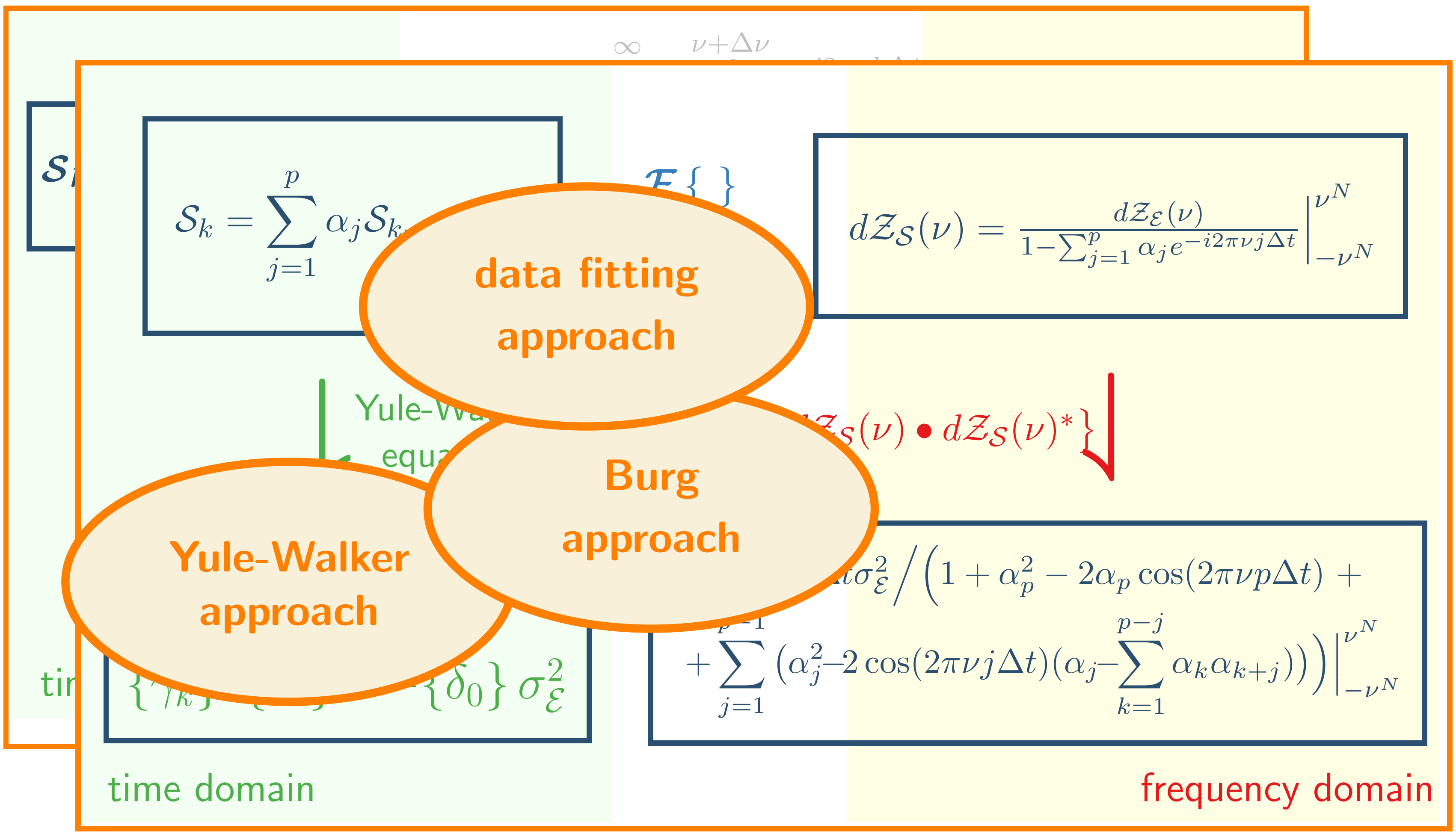
Magic square - AR(p) process

parametric spectral estimation



AR(p)-auto-regressive process — Magic Square

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Data Model - Robust Estimation

Observed Quantities:

$$\boxed{\mathcal{L}_k = \mathcal{S}_k + \mathcal{N}_k}$$

$\mathcal{S}_k$ ... stochastic process in AR representation

$$\mathcal{S}_k = \sum_{j=1}^{p} \alpha_j \mathcal{S}_{k-j} + \mathcal{E}_k$$

$\mathcal{E}_k$ ... innovation process

$\mathcal{N}_k$ ... additive process (noise)

Data model

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$\mathcal{E}_k$ ... innovation process

$\mathcal{N}_k$ ... additive process (noise)

Contamined real observed time series (e.g. GOCE)

$\mathcal{E}_k \sim F_{\mathcal{E}_k}(x)$ heavy-tailed distribution (e.g. Student distribution $F_{\mathcal{E}_k}^{t_r}(x)$)

$\mathcal{N}_k \sim F_{\mathcal{N}_k}(x)$ patchy outlier distribution

$$F_{\mathcal{N}_k}(x) = \alpha\delta_0 + \beta F_{pattern}(x) + (1-\alpha-\beta) F_{\mathcal{O}}^{\mathcal{N}(0,\sigma_{\mathcal{O}}^2)}(x)$$

δ_0 ... degenerated Dirac distribution

$F_{pattern}(x)$ ... degenerated fix pattern distribution

Data model

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δ_0 ... degenerated Dirac distribution

$F_{pattern}(x)$ ... degenerated fix pattern distribution

$\Longrightarrow$ **robust estimation of the stochastic process is essential**

Kleiner et.al. (1979): Robust Estimation of Power Spectra. *Journal of the Royal Statistical Society* B-41, 313-351

finite number of discrete measurements

a single realization ℓ_k of the random variable $\mathcal{L}_k$

$\{\ell_k\}_{\Delta t}$

$$L(\nu) = \Delta t \sum_{k=-\infty}^{\infty} \ell_k e^{-i2\pi\nu k\Delta t}$$

$\rightleftharpoons$

$$\ell_k = \int_{-\nu^N}^{\nu^N} L(\nu) e^{i2\pi\nu k\Delta t} d\nu$$

$L(\nu)\Big|_{-\nu^N}^{\nu^N}$

$M\left\{(\{l_u\} - \mu)(\{l_{u-k}\} - \mu)\right\}$

$\frac{1}{\Delta t} M\left\{L(\nu) \bullet L(\nu)^*\right\}$

$\{g_k\}$

$$psd(\nu) = \Delta t \sum_{k=-\infty}^{\infty} g_k \cos(2\pi\nu k\Delta t)$$

$\rightleftharpoons$

$$g_k = \int_{-\nu^N}^{\nu^N} psd(\nu) \cos(2\pi\nu k\Delta t) d\nu$$

$psd(\nu)\Big|_{-\nu^N}^{\nu^N}$

time domain

frequency domain

non-parametric spectral estimation

$$\{\ell_k\}_{\Delta t}$$

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averaging periodogram (Welch) approach

$$M\{(\{l_u\}-\mu)(\{l_{u-k}\}-\mu)\}$$

smoothed periodogram approach

Blackman-Tukey approach

$$\{g_k\}$$

$$psd(\nu)\Big|_{-\nu^N}^{\nu^N}$$

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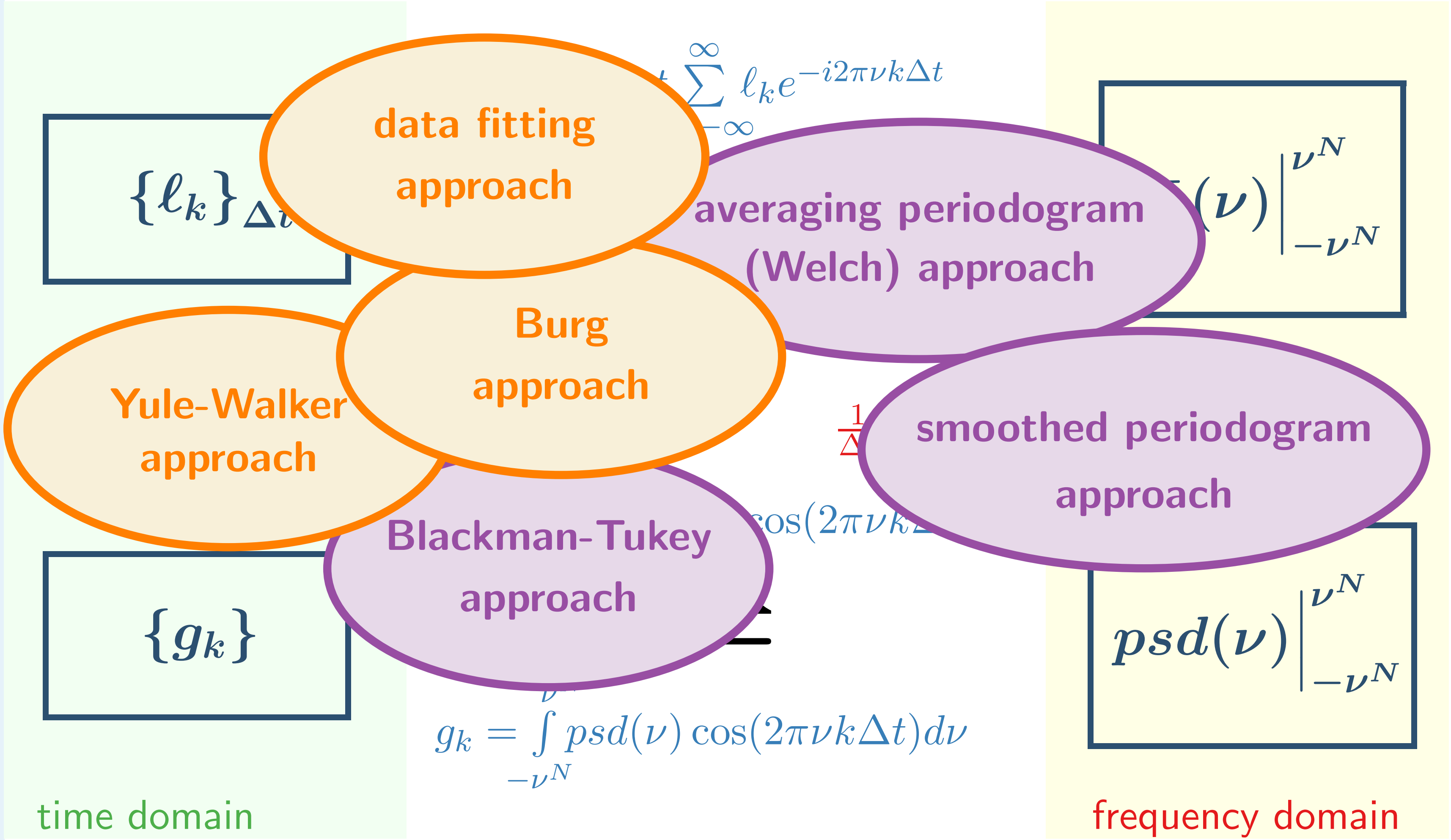
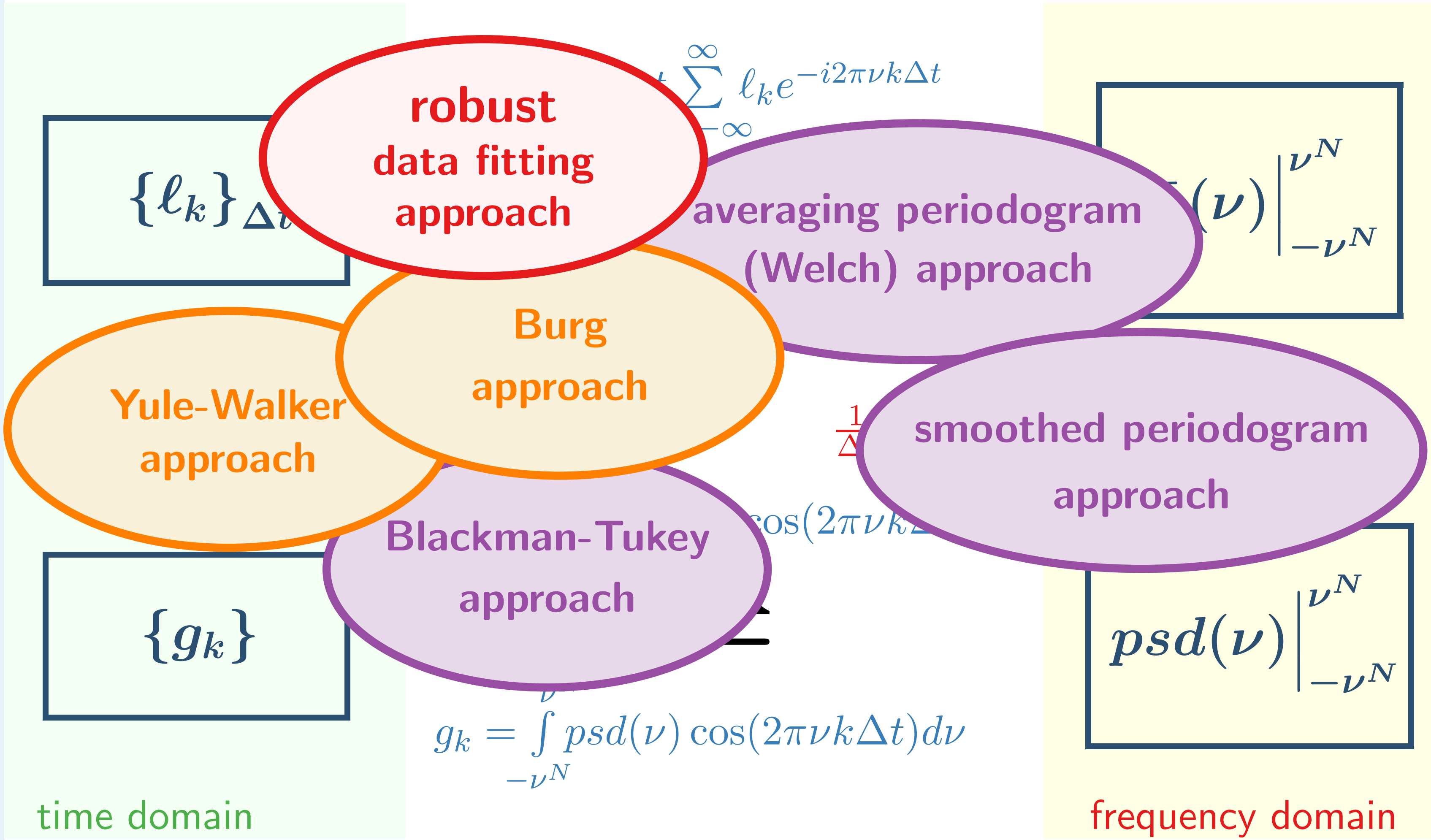
time domain

frequency domain

non-parametric spectral estimation
parametric spectral estimation



non-parametric spectral estimation
parametric spectral estimation



measurement l_k is a single realization of the random variable $\mathcal{L}_k$

Observation equations:

$$l_k + v_k = \sum_{j=1}^{p} \alpha_j l_{k-j} = [l_{k-1} \ldots l_{k-p}] \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_p \end{bmatrix} := \boldsymbol{a}_k^T \boldsymbol{\alpha}$$

Optimization principle: $$\inf_{\tilde{\boldsymbol{\alpha}}} \sum_{i=p+1}^{\#obs} \rho\left(\frac{v_k}{s_{\mathcal{E}}}\right)$$

Normal equations: $$\sum_{i=p+1}^{\#obs} \boldsymbol{a}_k \psi\left(\frac{v_k}{s_{\mathcal{E}}}\right)$$

$\rho\left(\bar{v}_k\right)$ ... loss function $\qquad \psi\left(\bar{v}_k\right) = \dfrac{\partial\rho(\bar{v}_k)}{\partial\boldsymbol{\alpha}}$ ... influence function

Influence function:

$$\psi_{L2}(\overline{v_k}) = \overline{v_k}$$ L2-estimator

$$\psi_{L1}(\overline{v_k}) = \text{sign}(\overline{v_k})$$ L1-estimator

$$\psi_{H}(\overline{v_k}) = \begin{cases} \overline{v_k} & |\overline{v_k}| < k \\ \text{sign}(\overline{v_k}) & |\overline{v_k}| \geq k \end{cases}$$ Huber-estimator

$$\psi_{R}(\overline{v_k}) = \begin{cases} \overline{v_k} & |\overline{v_k}| < k \\ 0 & |\overline{v_k}| \geq k \end{cases}$$ $k\sigma$-rejection-estimator

Influence function:

$$\psi_{L2}(\overline{v_k}) = \overline{v_k}$$ L2-estimator

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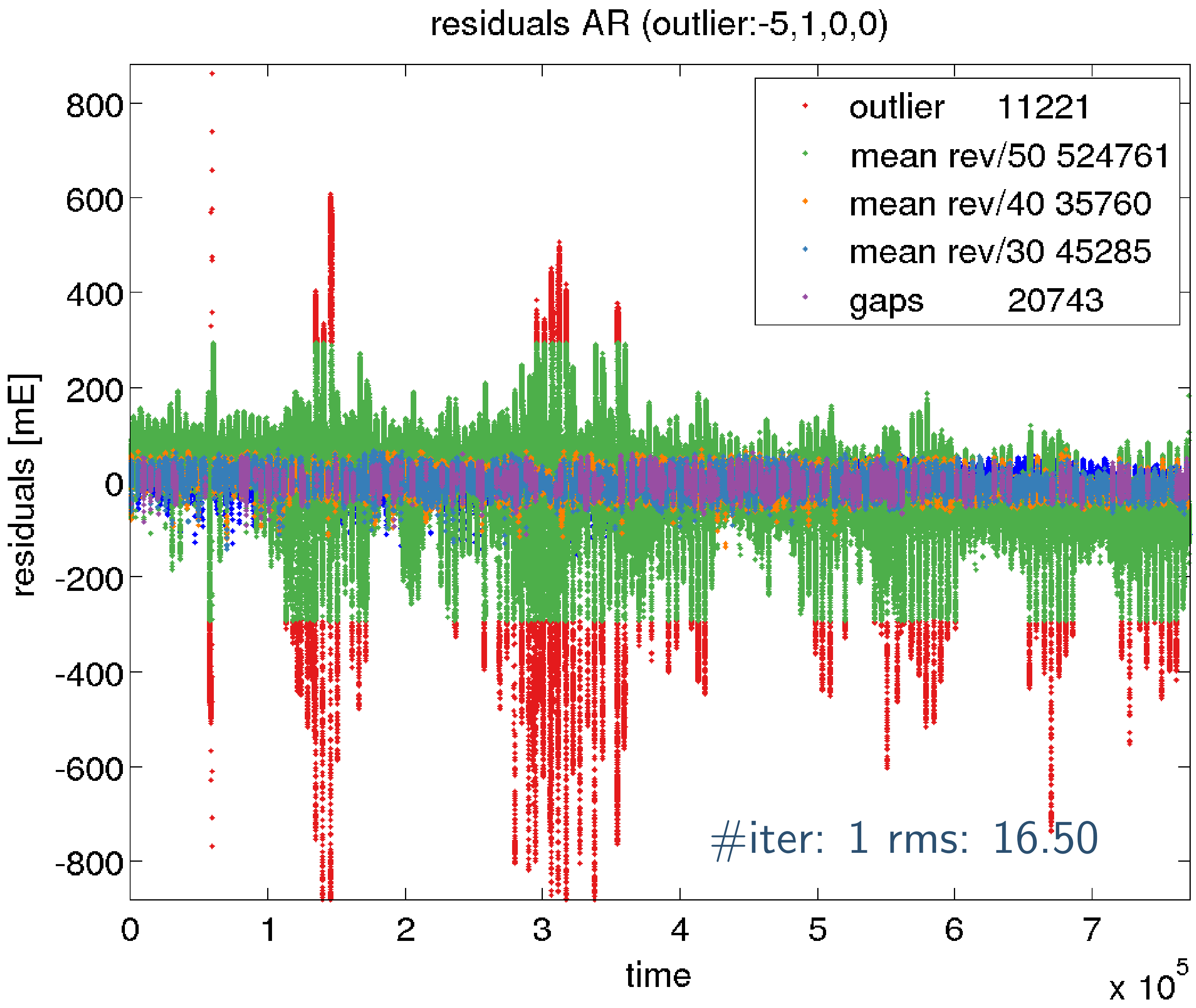
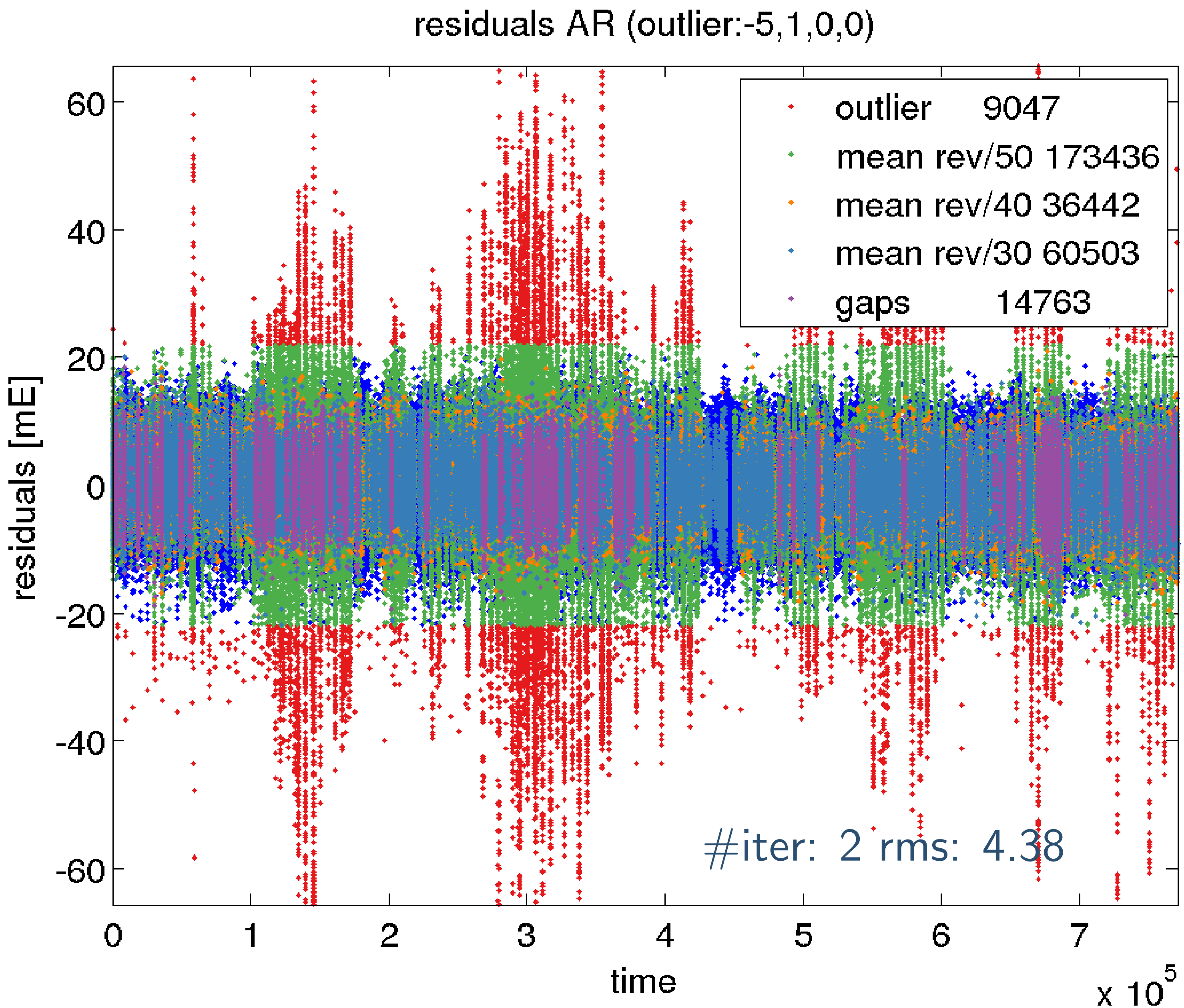
GOCE-LOOC: $k\sigma$-rejection-estimator (single and area-mean)
AR(p) processes up to degree 2000
ARI(i,p) integrated AR-processes - filter cascades

Application to GOCE residual time series

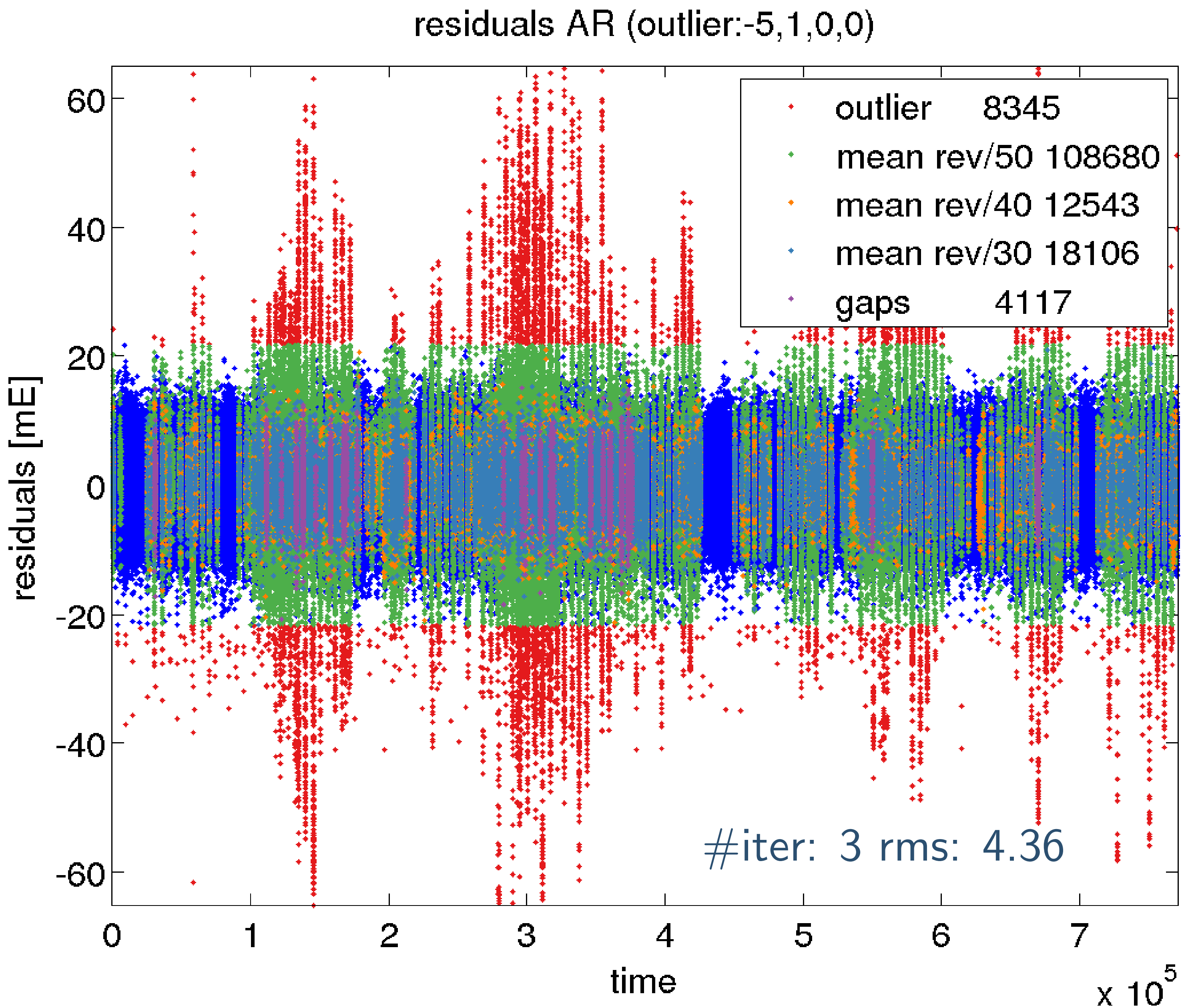
Filter estimation: Segment 68-yy



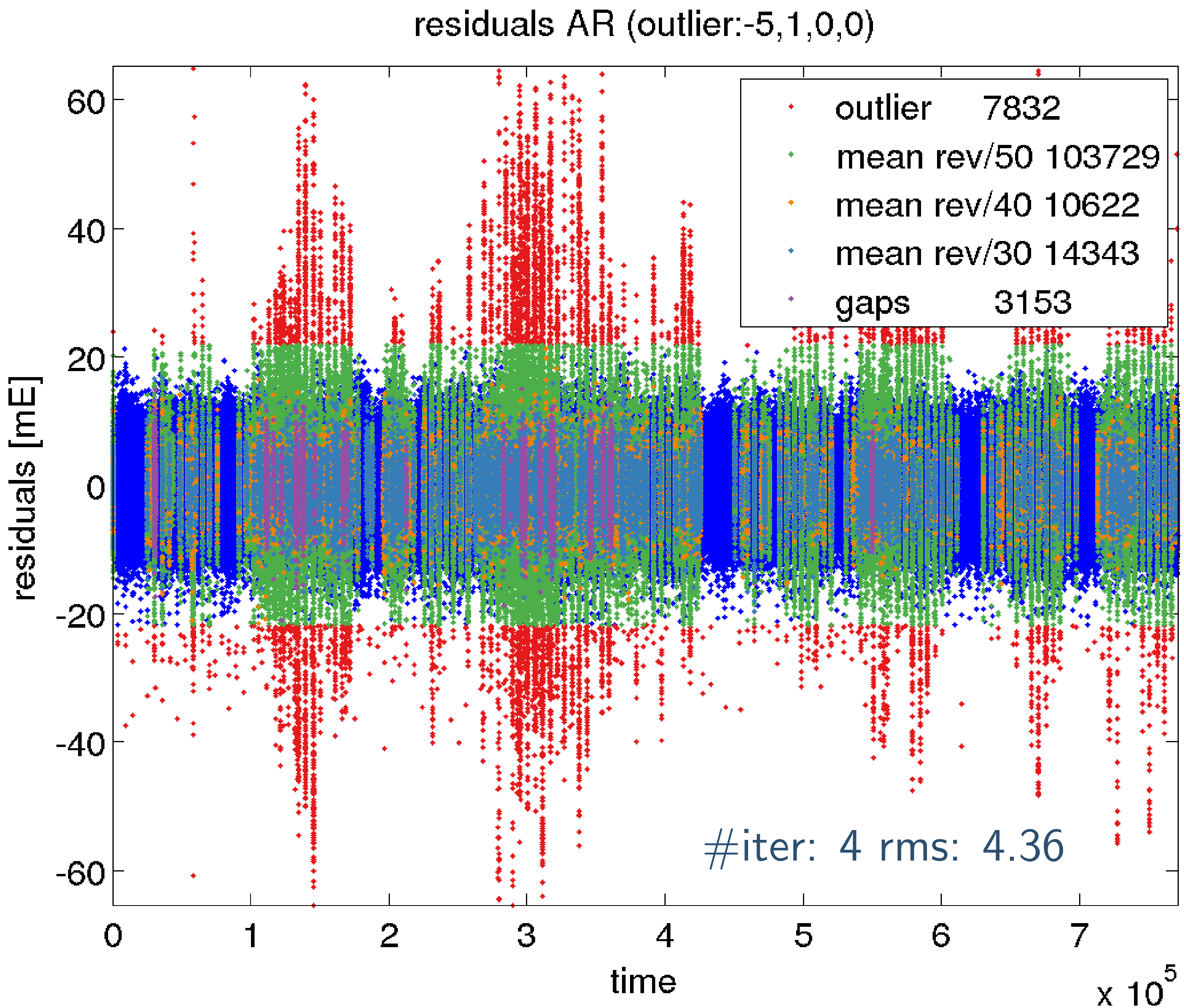
Filter estimation: Segment 68-yy



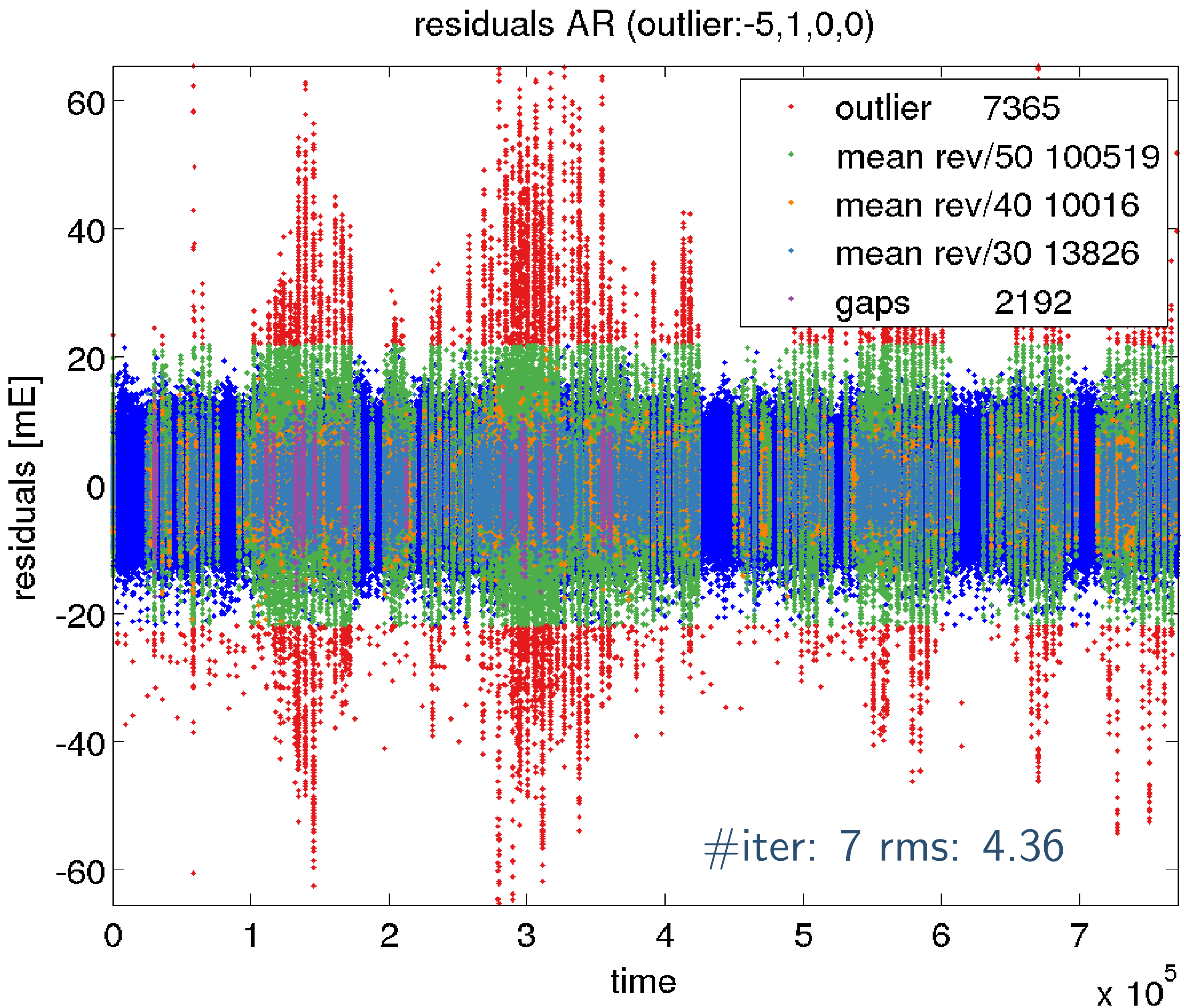
Filter estimation: Segment 68-yy



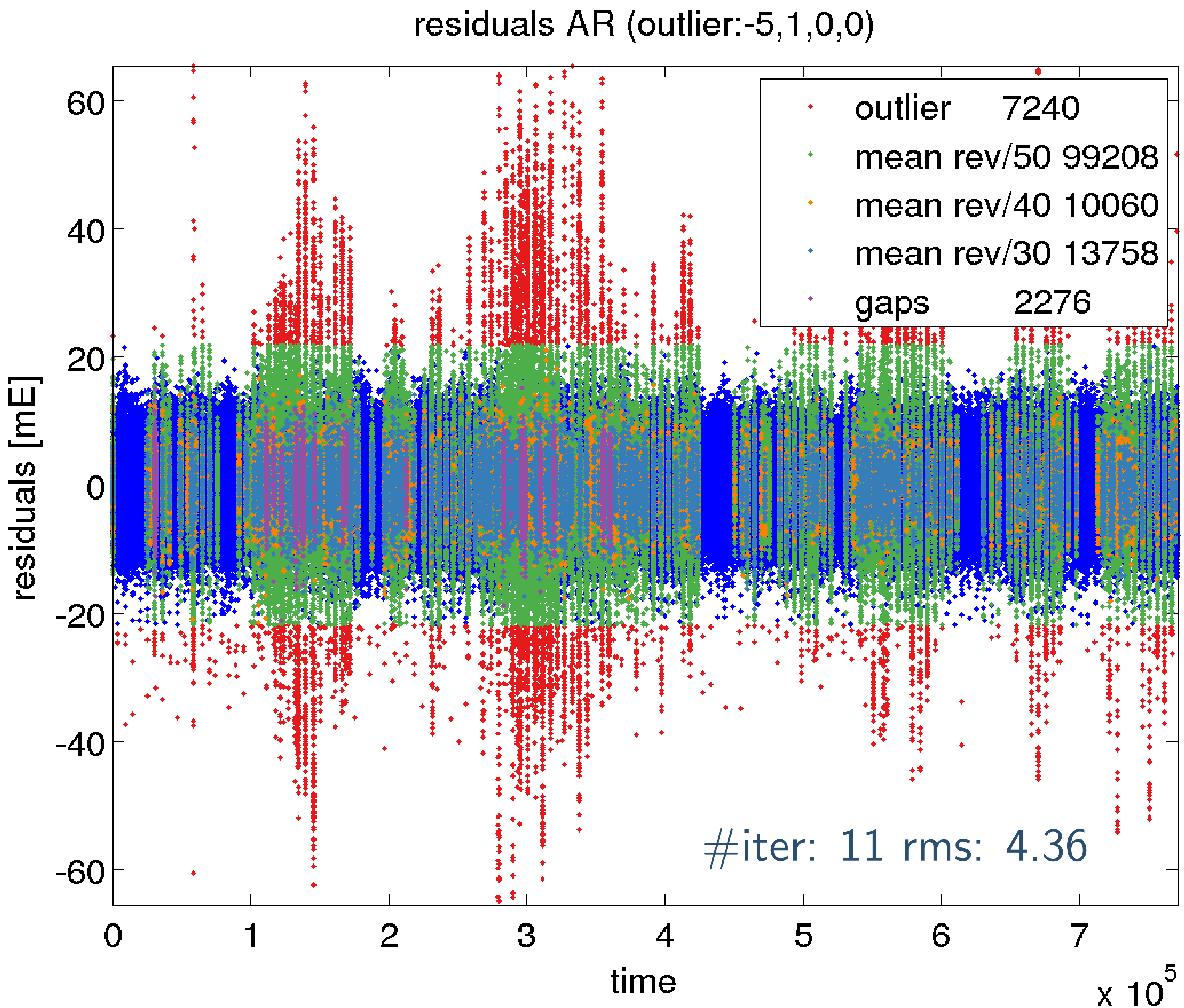
Filter estimation: Segment 68-yy



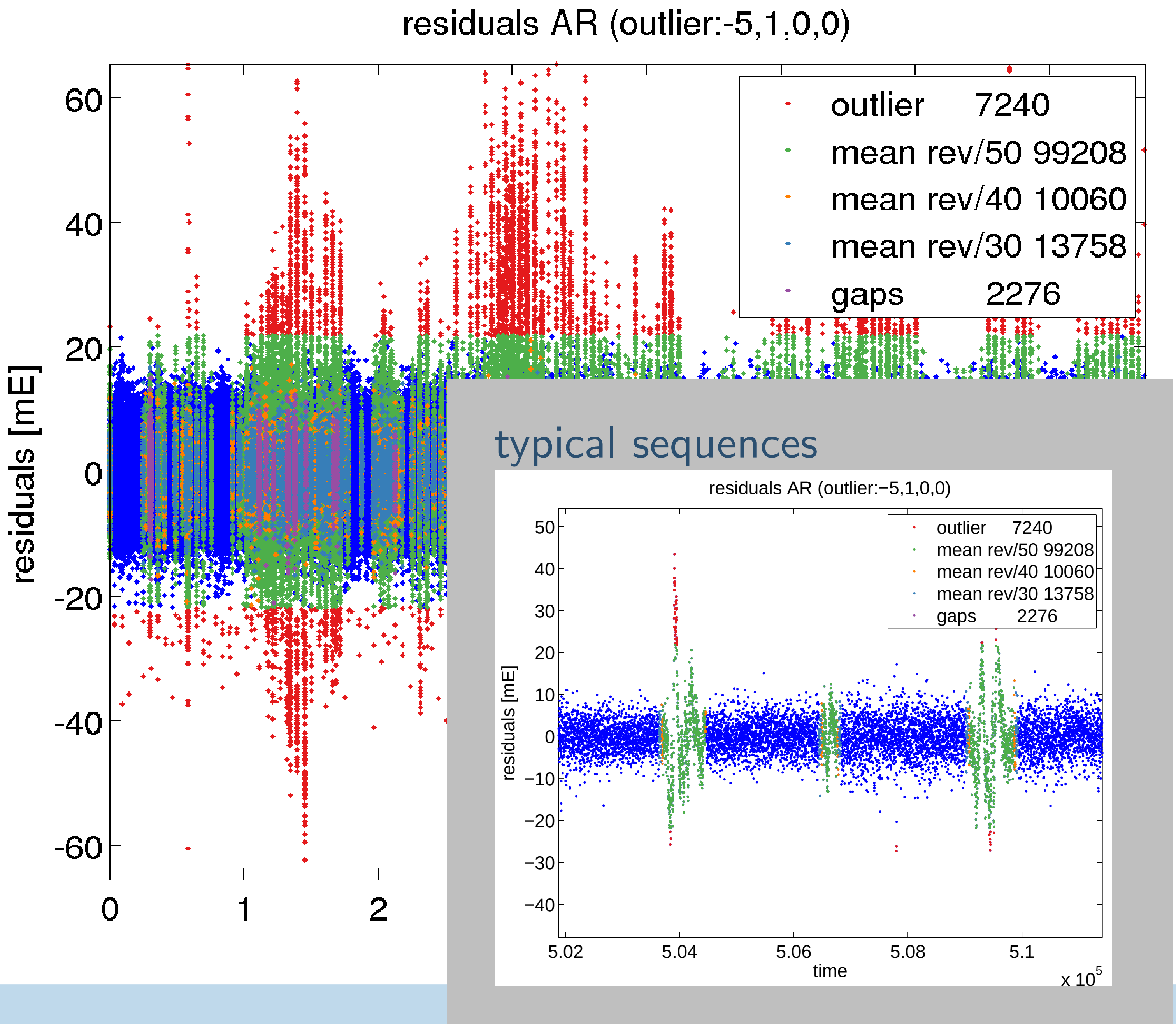
Filter estimation: Segment 68-yy



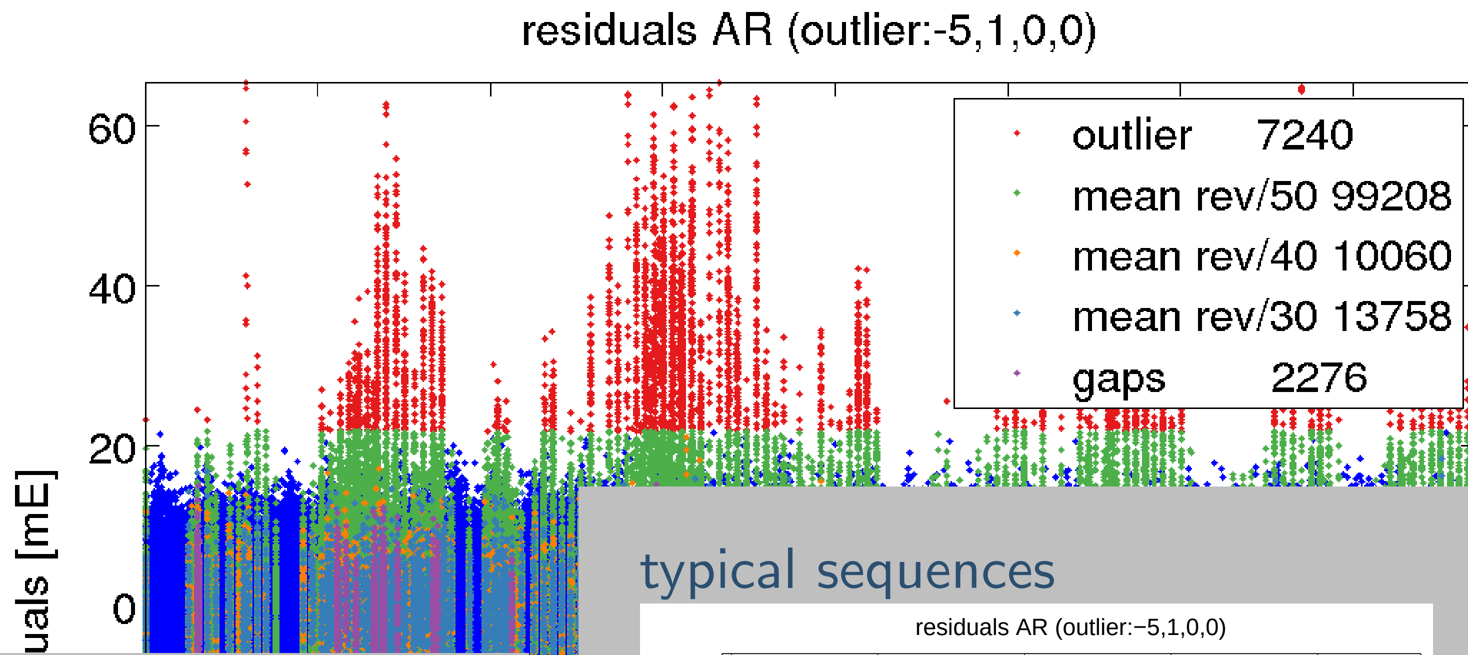
Filter estimation: Segment 68-yy



Filter estimation: Segment 68-yy



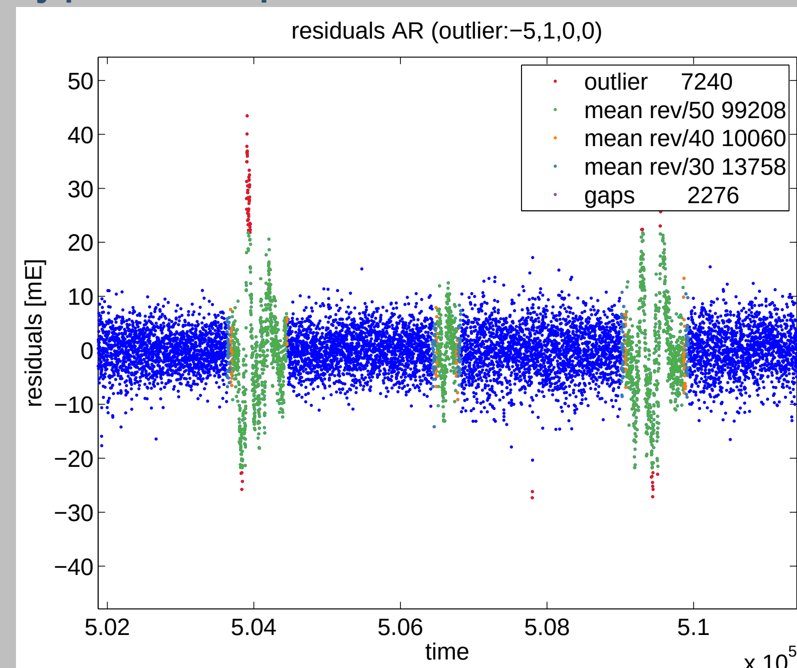
Filter estimation: Segment 68-yy



Statistics: Segment 68-yy

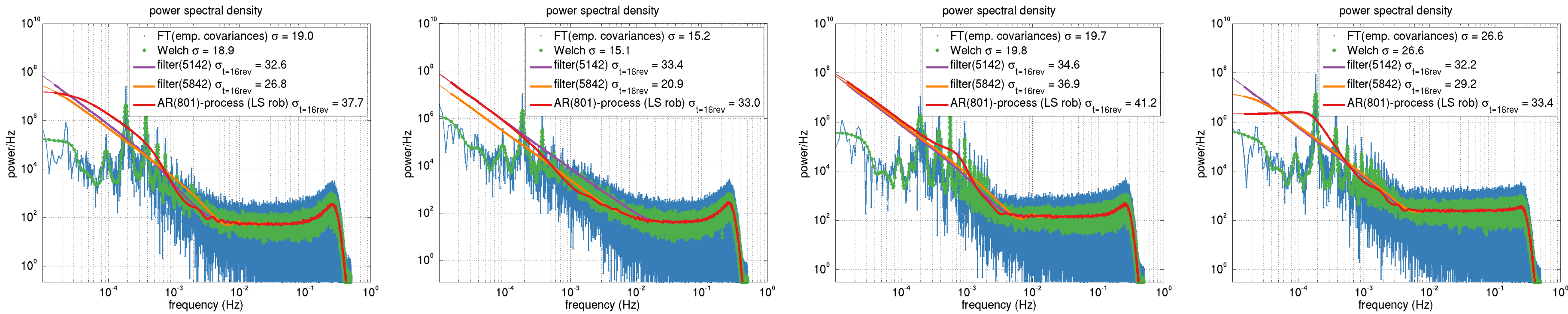
#data:	771579
#conspicuous data:	122731
	17 %
std (1^{st} iteration):	16.50 [mE]
std (11^{th} iteration):	4.36 [mE]

typical sequences

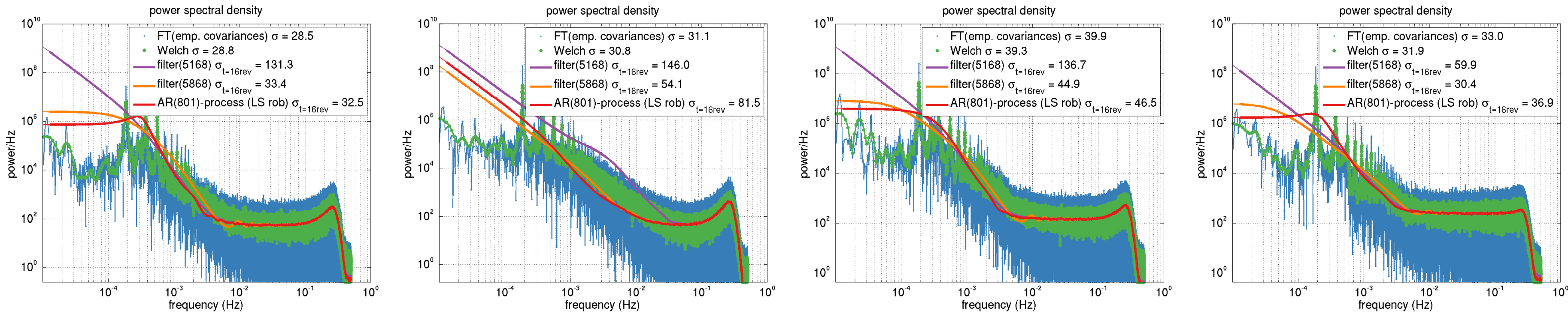


GOCE AR-filter psd

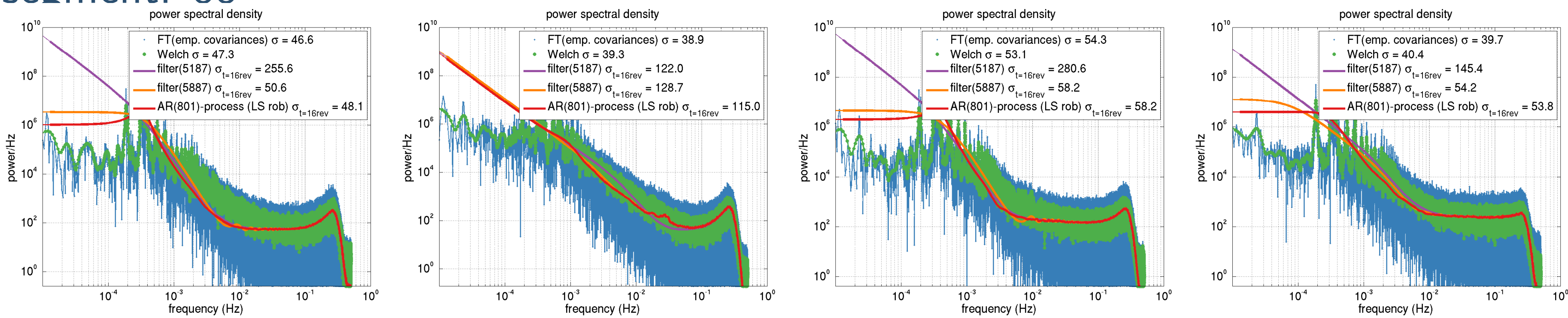
segment: 42



segment: 68



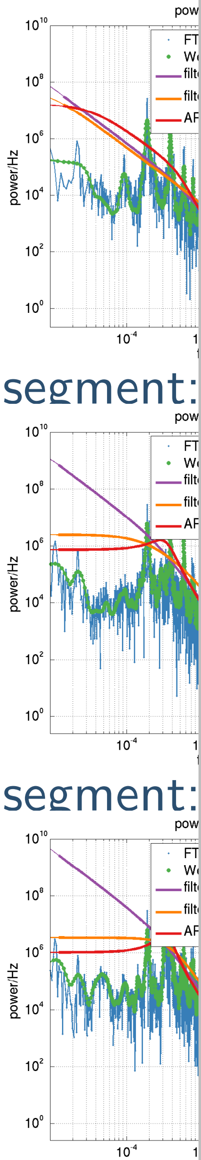
segment: 88

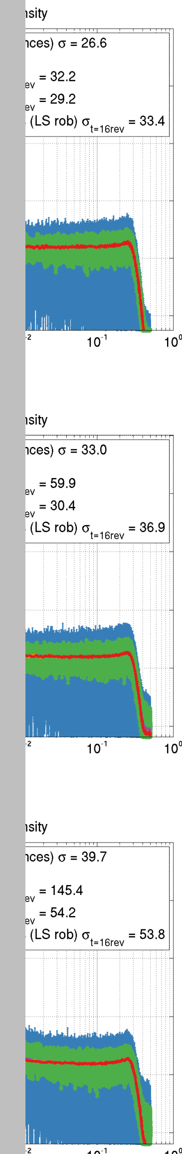


segment:

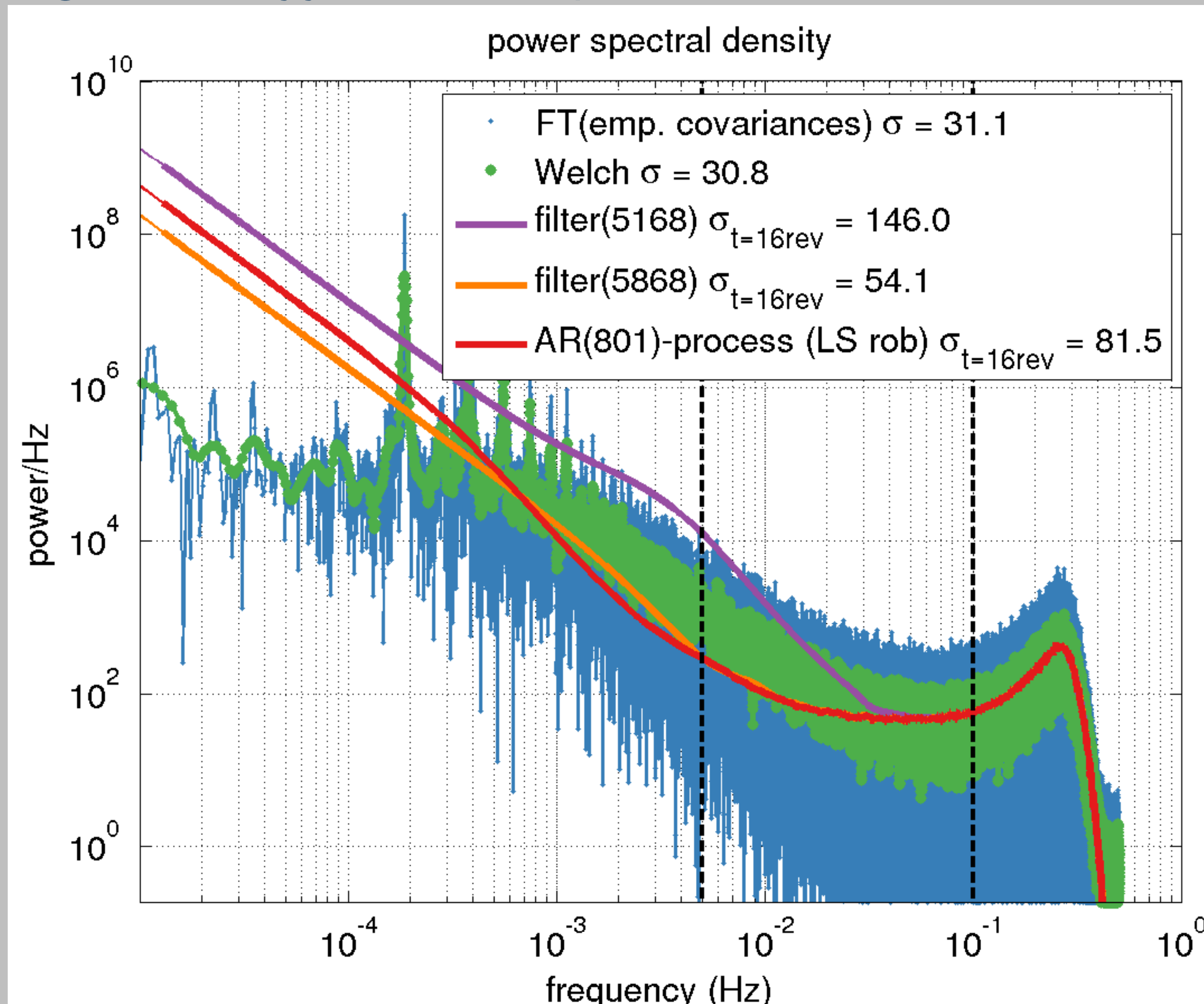
segment:

segment:



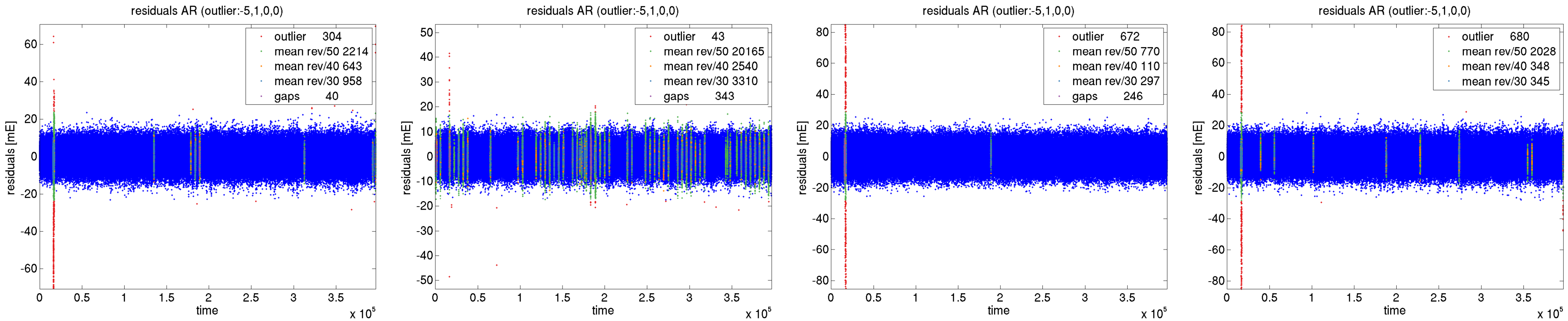


Segment 68-yy: AR filter psd

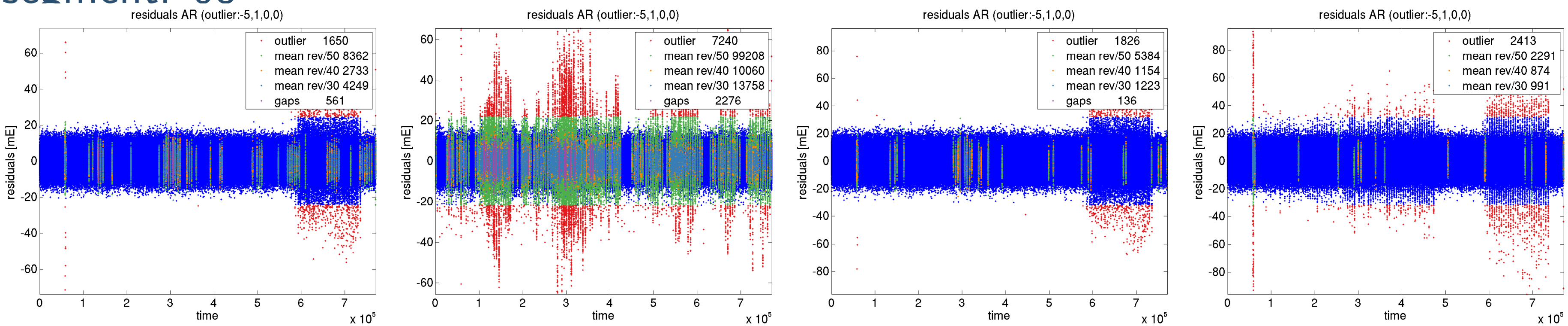


GOCE conspicuous data identification

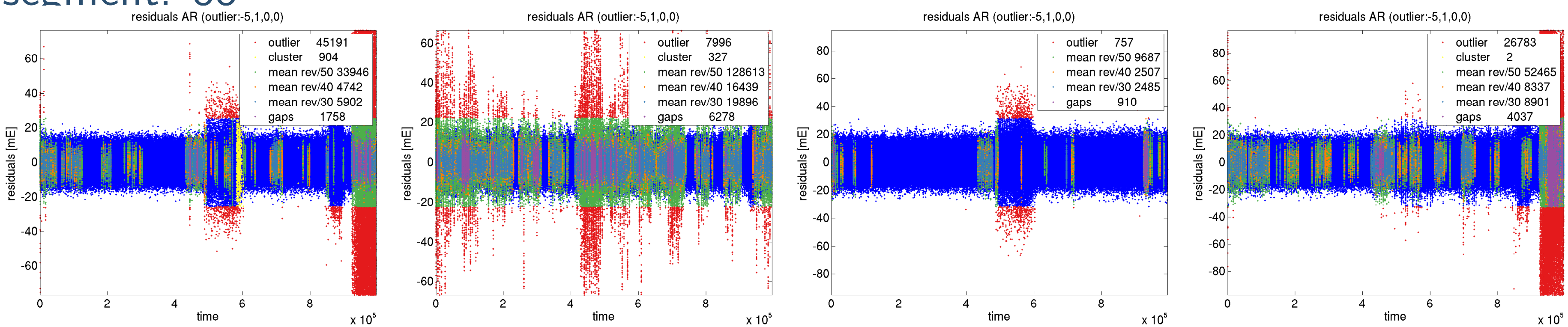
segment: 42



segment: 68

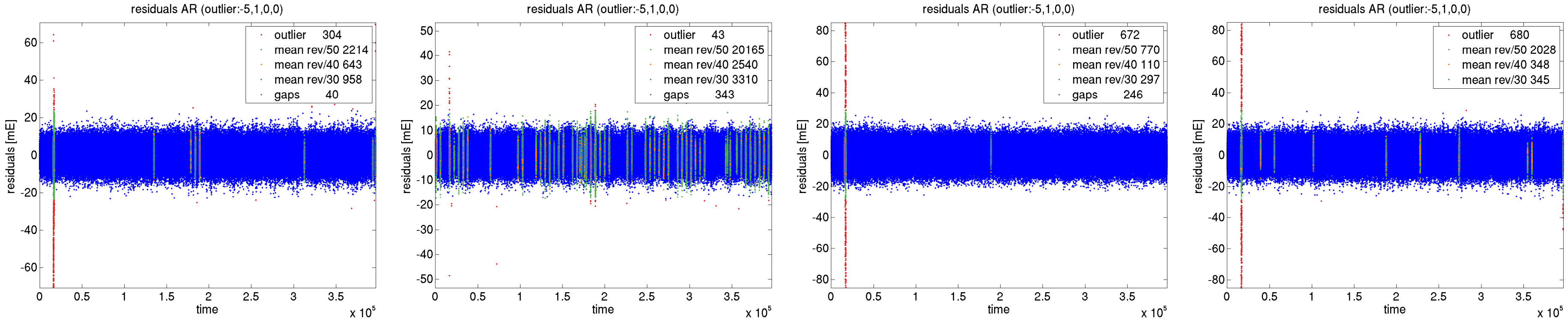


segment: 88



GOCE conspicuous data identification

segment: 42



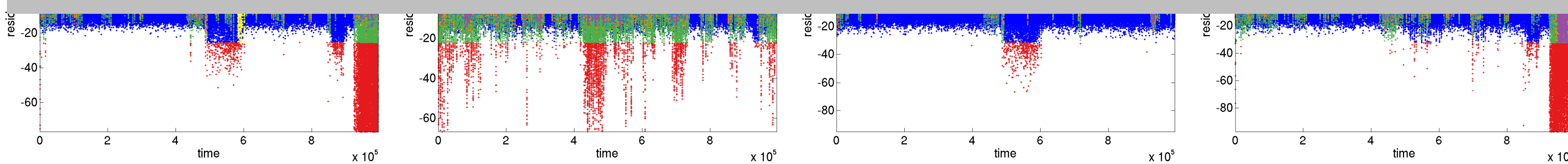
segment: 68

residuals AR (outlier:-5,1,0,0) residuals AR (outlier:-5,1,0,0) residuals AR (outlier:-5,1,0,0) residuals AR (outlier:-5,1,0,0)

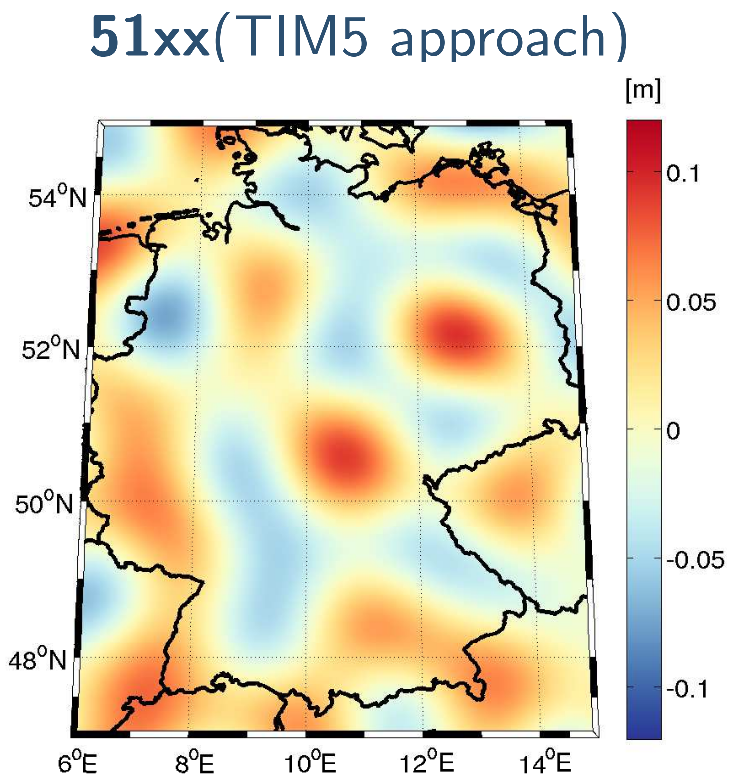
Statistics: LOOC 13-Jun-2012 — 21-Oct-2013

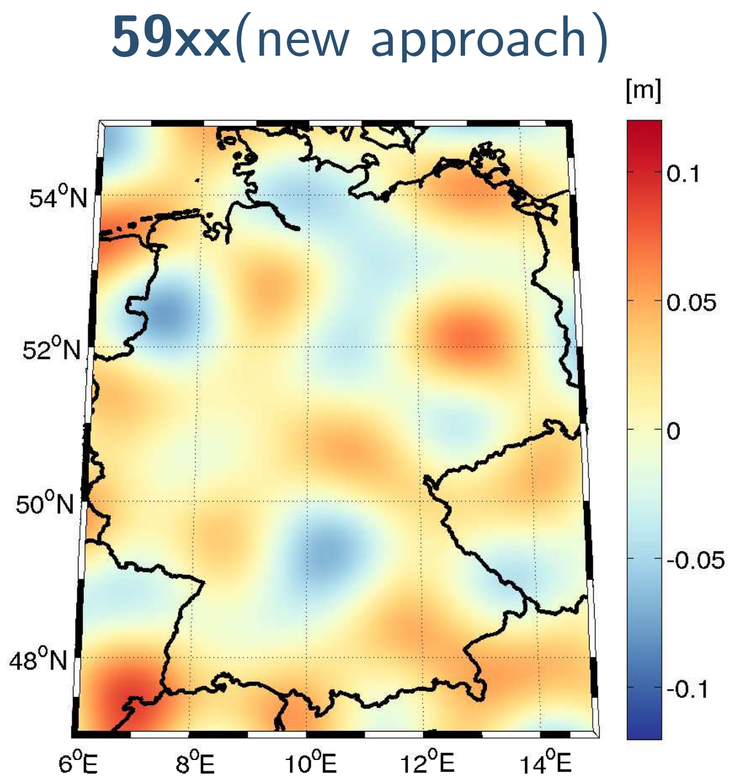
#data: 40,578,761 segments: 48

	xx	yy	zz	xz
#conspicuous data:	2,576,822	7,322,250	1,397,442	1,979,398
	6.4 %	18.0 %	3.4 %	4.9 %
std noise [mE]:	5.0	4.1	6.1	5.8



First Reslust: rms 59xx-EGM08 51xx-EGM08





Area:	model	std [m]	Area:	model	std [m]
North Atlantik	51xx	0.032	Germany	51xx	0.033
(d/o 200)	59xx	0.029	(d/o 200)	59xx	0.028

$\Longrightarrow$ expected gain of accuracy for the reprocessed data (5-15%)

Brockmann et.al. (EGU2015-12307): A case study on the potential of robust decorrelation filter design for a reprocessing of a gravity field model from GOCE data - presentation on Tuesday

Resumé: robust filter estimation

- **advanced outlier detection:**
  − much more conspicuous data (6% ⇒ 18%)
  + separation of effects (outlier, gap, disruption, ...)
- **optimized AR filter:**
  + optimal relative weighting between the components
  + gain of accuracy for the GOCE-TIM models ($\sim 10\%$)

quality vs. quantity

Resumé: robust filter estimation

- **advanced outlier detection:**
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quality vs. quantity

Thank you for your attention