

Measuring AFM wrong (and perhaps right)

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Scanning Probe Microscopy

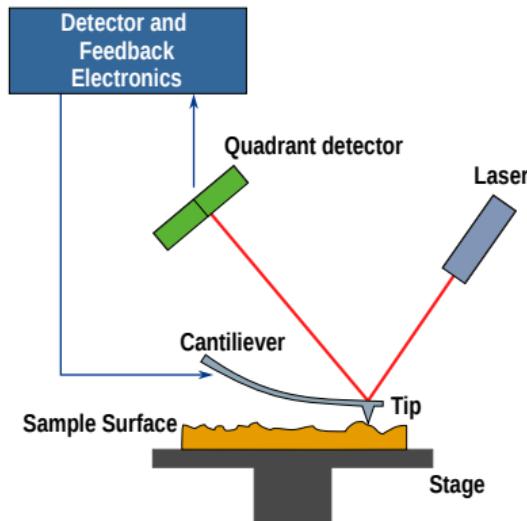
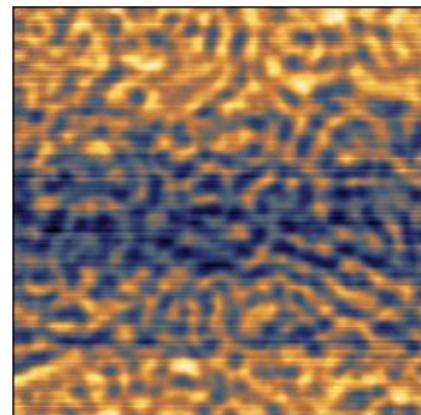
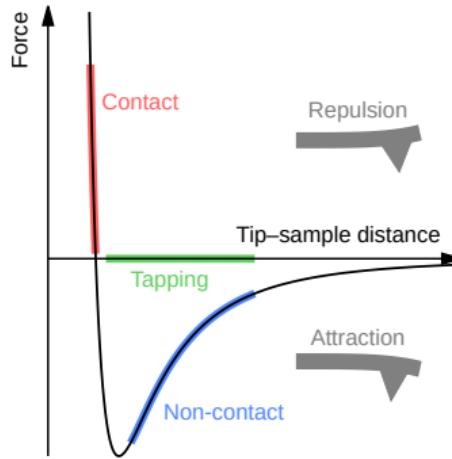


Image formation: Scanning the surface line by line



Anisotropy: Fast & slow axis

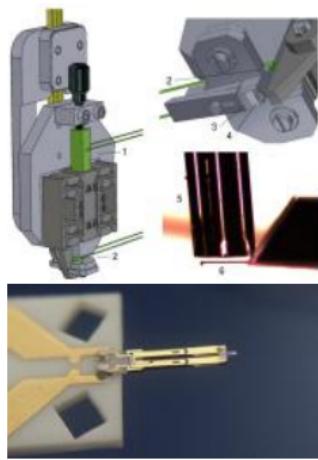
Open & closed loop

Techniques: Mechanical, electrical, magnetic, thermal, optical, ...

More in Petr Klapetek's lecture on Friday!

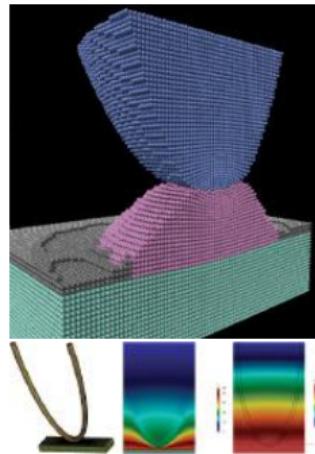
Quantitative SPM

Hardware



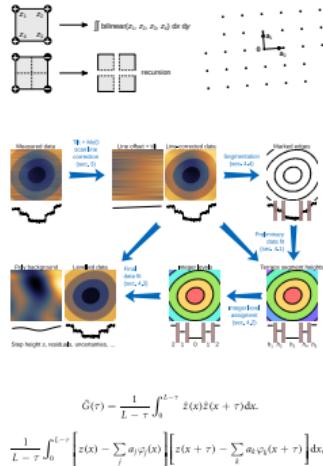
Stage & head
Probes
Electronics
Environmental
...

Physics



Probe-sample
interaction
Atomistic modelling
Molecular dynamics
FEM & FDTD
...

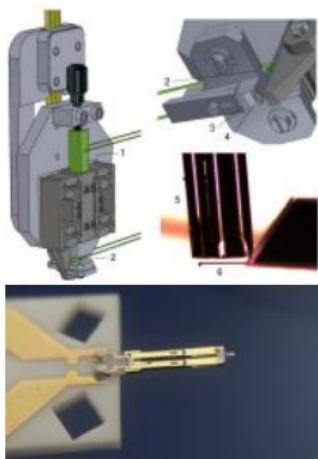
Algorithms



Filtering &
preprocessing
Feature recognition
Model fitting
Statistical
...

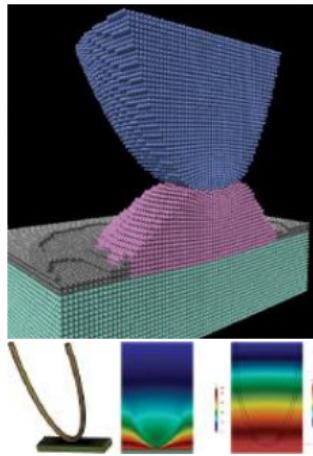
Quantitative SPM

Hardware



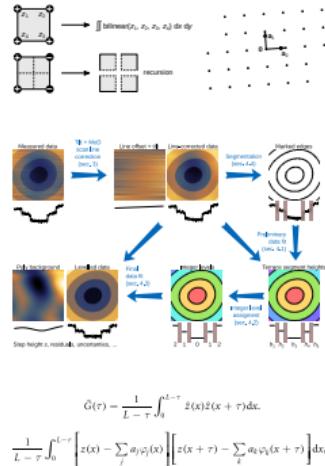
Stage & head
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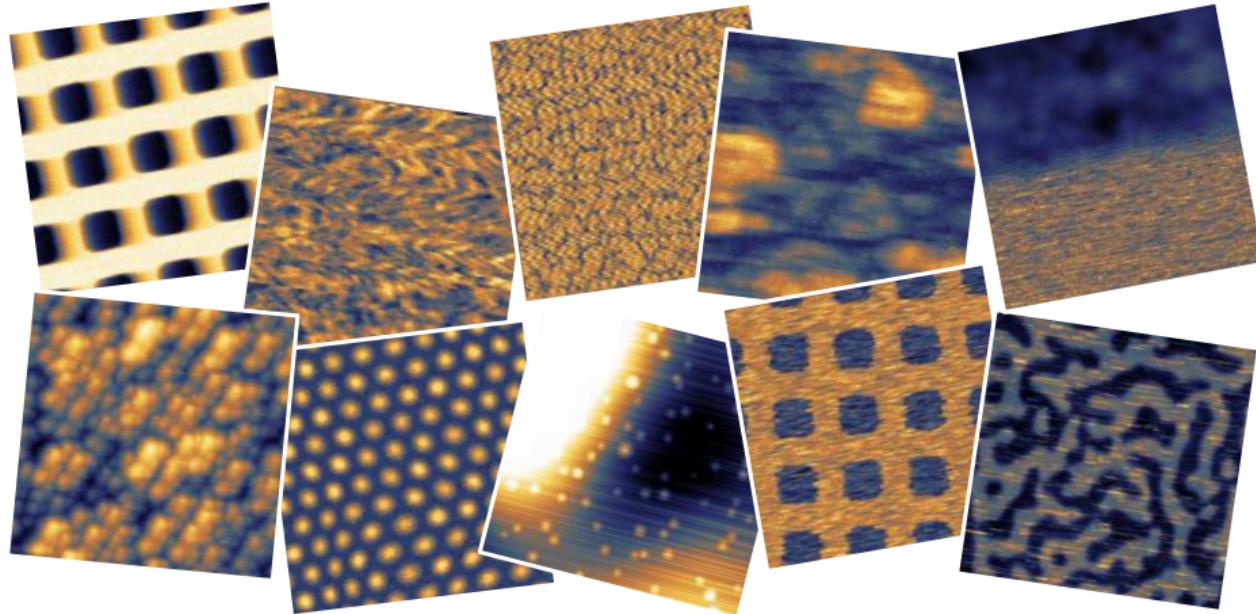
Filtering &
preprocessing
Feature recognition
Model fitting
Statistical
...

Secret ingredient



This talk?

Bad data? Easy!



Many effects conspire to sabotage our SPM measurements

Mechanical & electromagnetic noise, laser interference, cross-talk, changes in probe properties & contact, contamination & tip convolution, bad feedback parameters, hysteresis & non-linearity, creep, aging, topography artefacts, ...

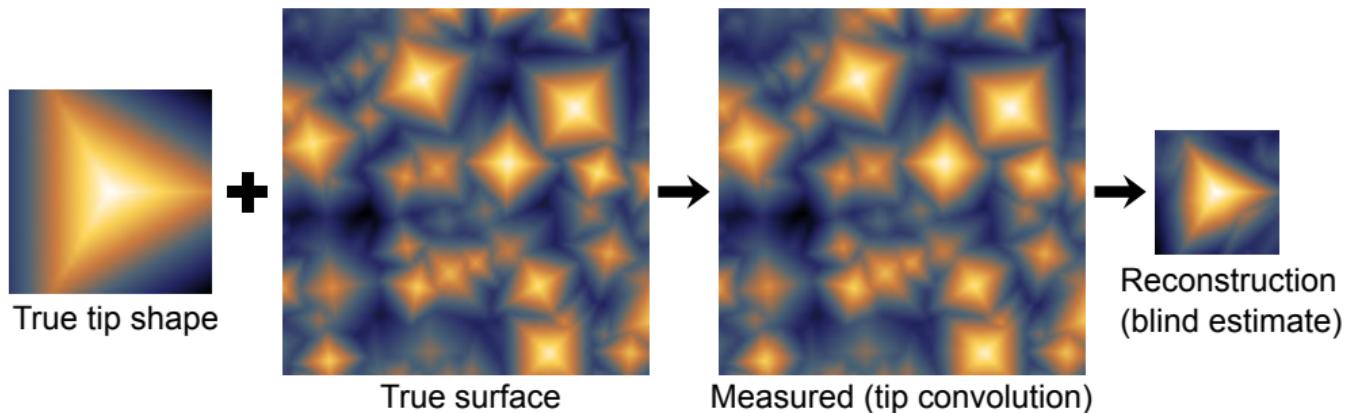
Good data?

Tip convolution → convolution artefacts



Blind estimation

of tip shape using tip imaging
by sharp surface features

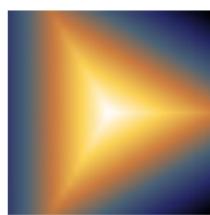


Good data?

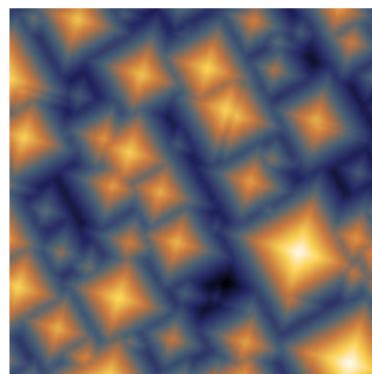
Tip convolution → convolution artefacts

Blind estimation

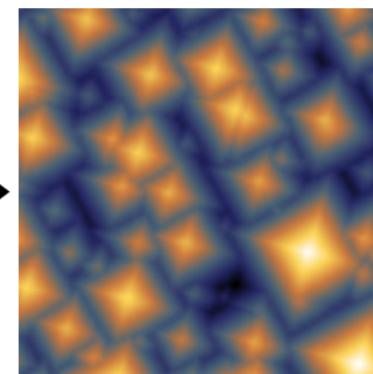
of tip shape using tip imaging
by sharp surface features



True tip shape



True surface



Measured (tip convolution)

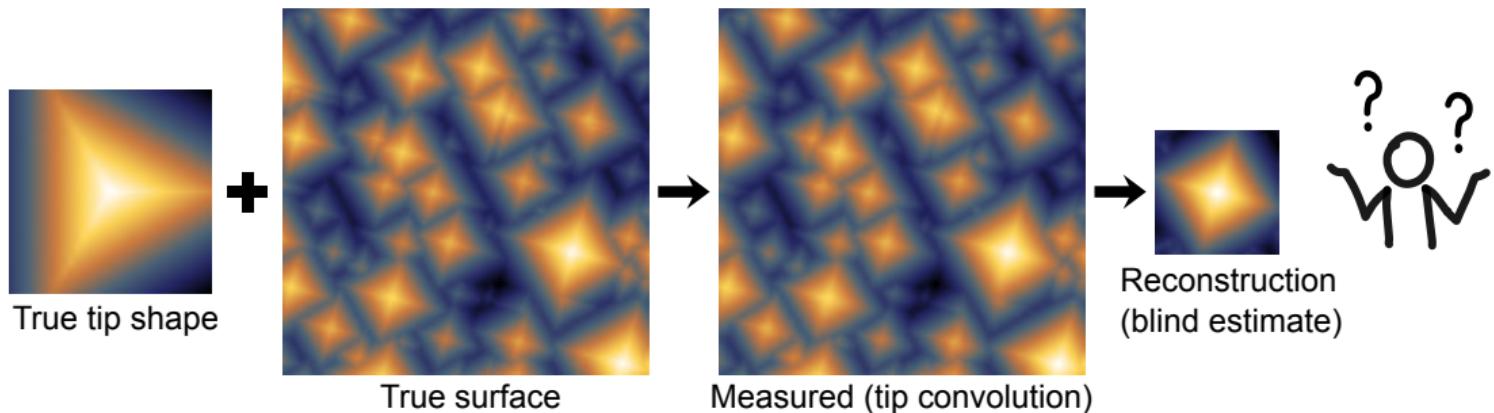
Good data?

Tip convolution → convolution artefacts



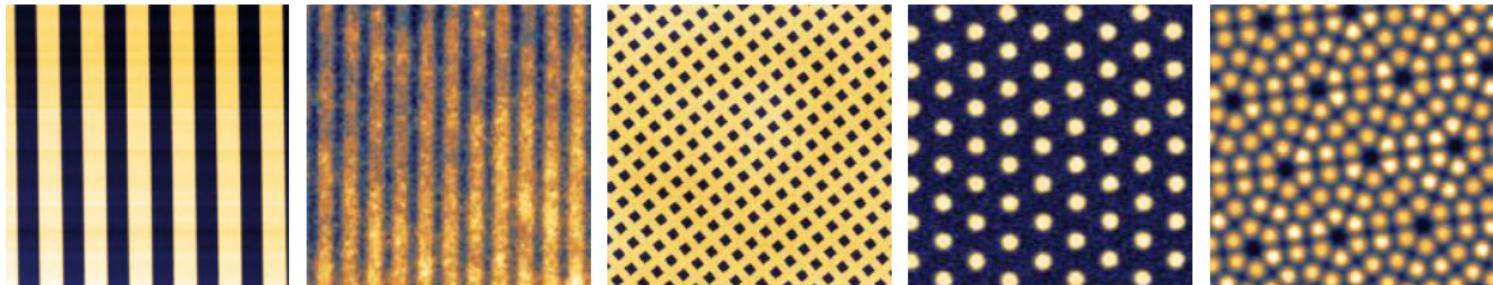
Blind estimation

of tip shape using tip imaging
by sharp surface features



Similar: tip transfer/point spread function, etc.

Periodic structures



Different origins:

- ▶ lithography & laser interference
- ▶ atomic lattices
- ▶ self-organised wrinkles, domains, ...

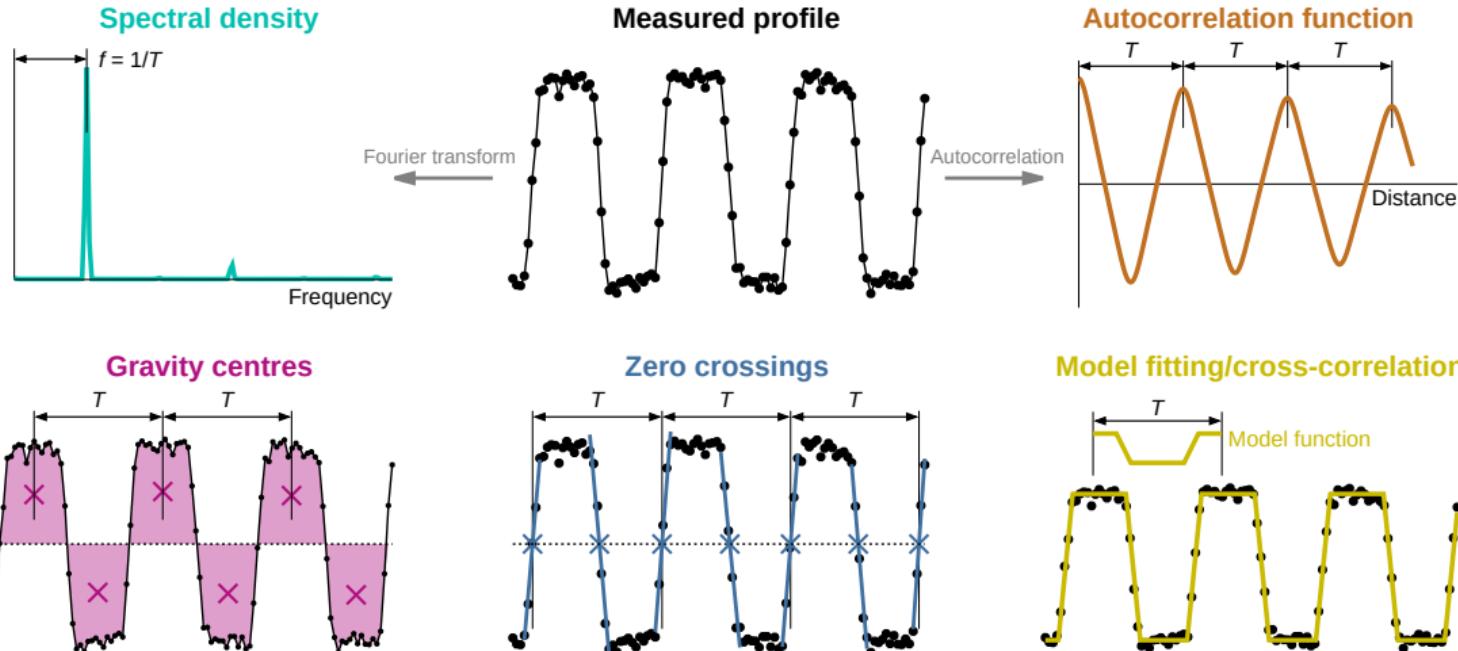
Data evaluation generally similar.

Pitch & height standards – but maybe not both from one measurement.

Different purposes:

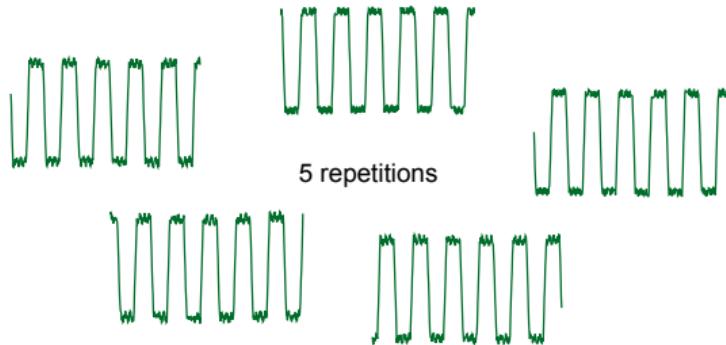
- ▶ studying a structure/process
- ▶ instrument calibration
- ▶ *ex post* data correction

Evaluation of period/pitch



- ▶ Feature identification (direct space)
- ▶ Fourier transform
- ▶ Autocorrelation – not widely used

More is better



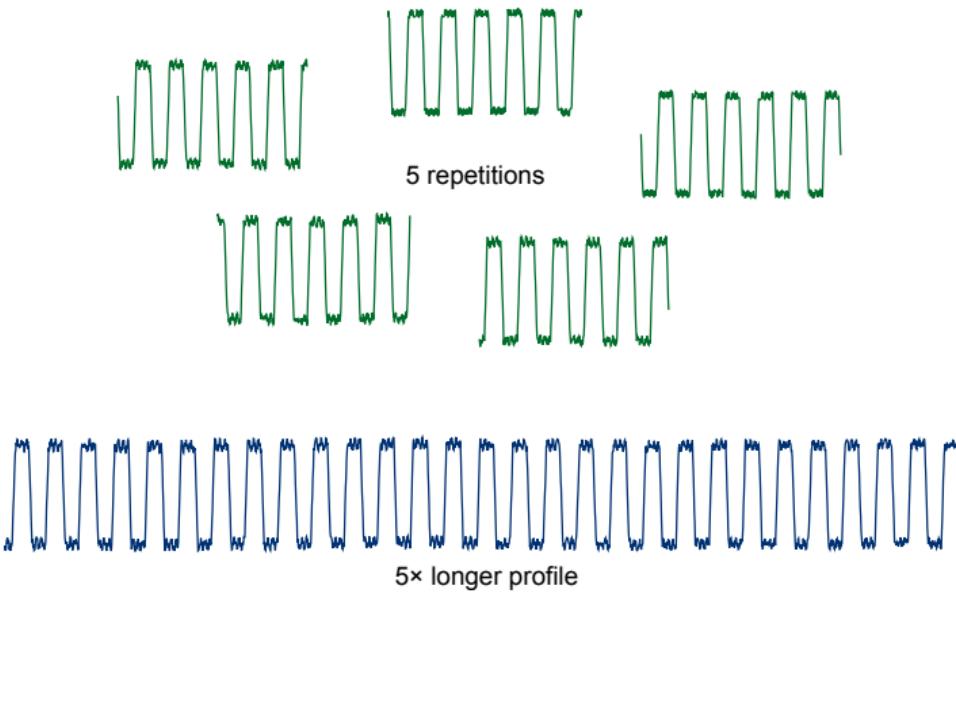
Warm up question

Measuring 5× is about:

- (a) $\sqrt{5}\times$ worse,
- (b) the same,
- (c) $\sqrt{5}\times$ better,
- (d) 5× better,
- (e) $\infty\times$ better

than measuring once.

More is better



Warm up question

Measuring 5× is about:

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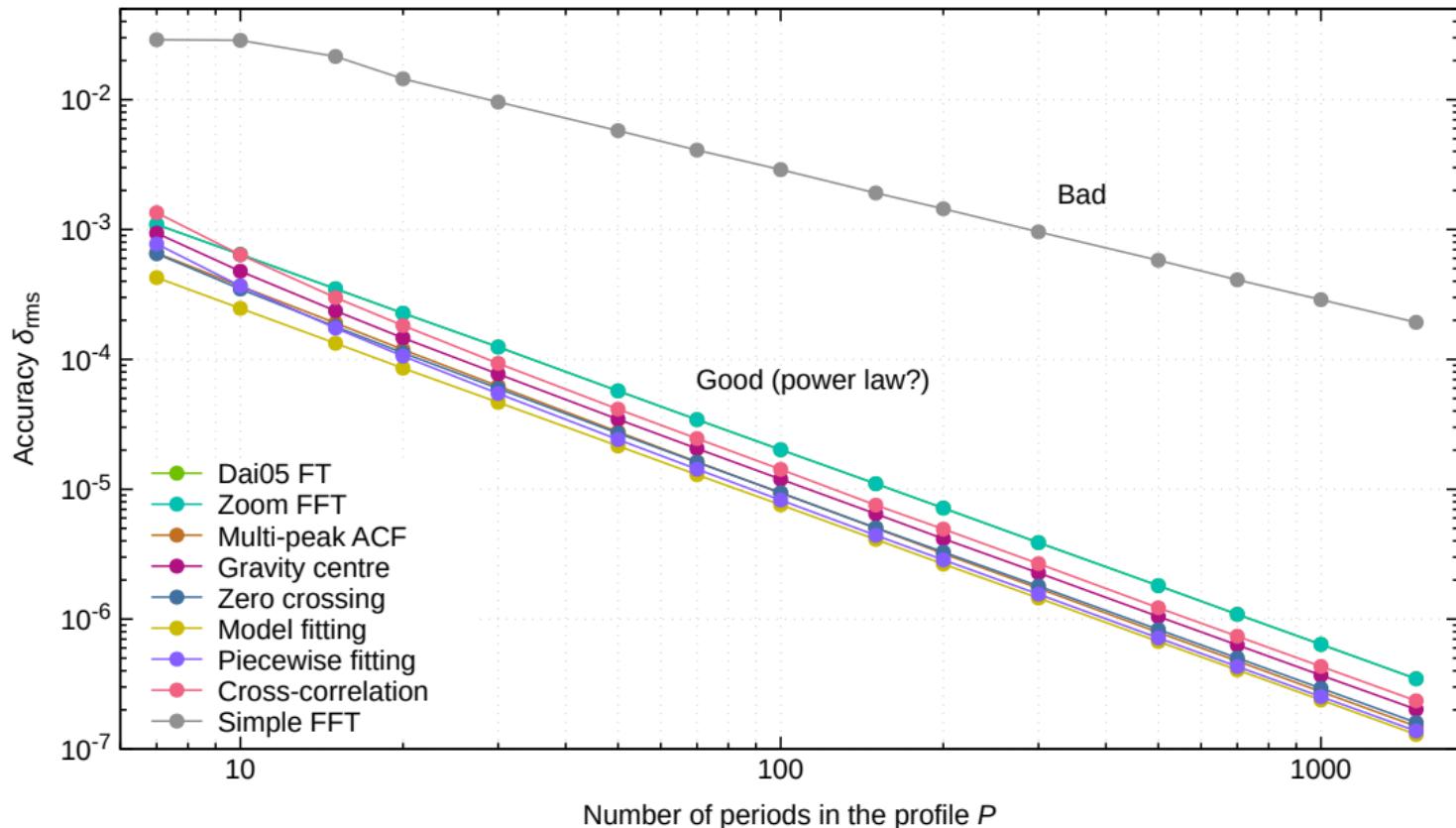
than measuring once.

One longer profile is:

- (a) 5× worse,
- (b) $\sqrt{5}\times$ worse,
- (c) the same,
- (d) $\sqrt{5}\times$ better,
- (e) 5× better.

than measuring 5 shorter ones.

Scaling



Scaling power

Model $x_n = nT$

$$\text{Estimate } \hat{T} = \sum_{n=1}^P nx_n \Big/ \sum_{n=1}^P n^2$$

$$\text{Dispersion } \Delta_T^2 = \sum_{n=1}^P \left(\frac{\partial \hat{T}}{\partial x_n} \right)^2 \Delta_x^2 = \Delta_x^2 \Big/ \sum_{n=1}^P n^2 \approx \frac{3}{P^3} \Delta_x^2$$

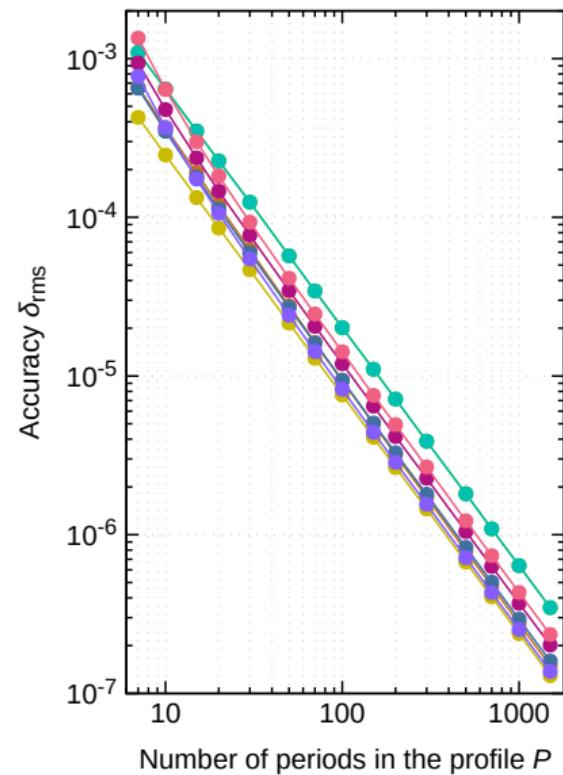
$$\text{Scaling } \Delta_T \approx \frac{1}{P^{3/2}} \sqrt{3} \Delta_x$$

T – period (fitted)

Δ_T – standard deviation of T

Δ_x – location error in x

P – number of periods



Scaling power

Model $x_n = nT$

$$\text{Estimate } \hat{T} = \sum_{n=1}^P nx_n \Big/ \sum_{n=1}^P n^2$$

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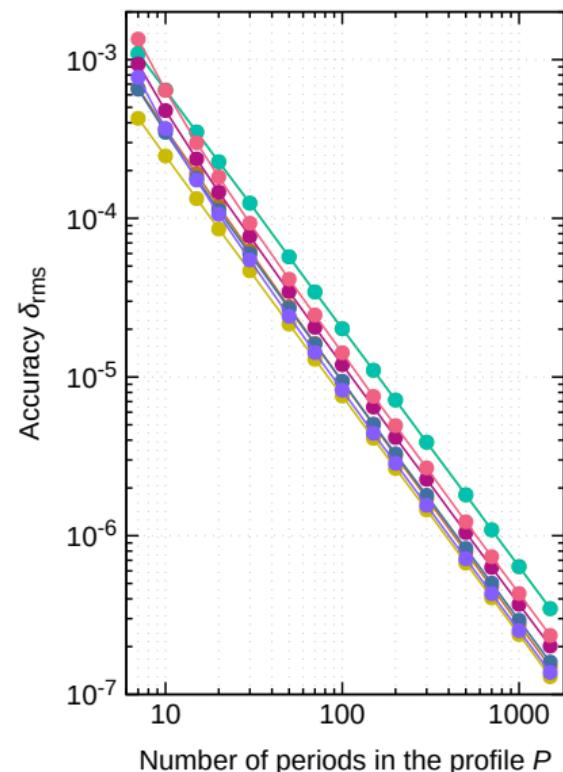
Δ_x – location error in x

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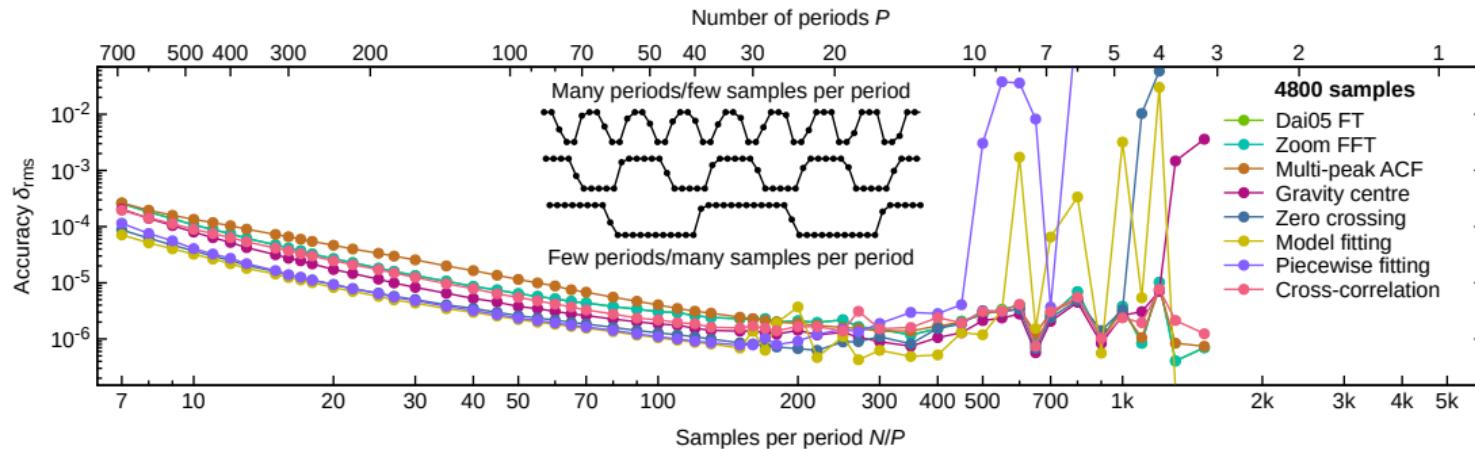
Scaling powers

- ▶ Single long profile: $-3/2$
- ▶ Repeated measurement: $-1/2$

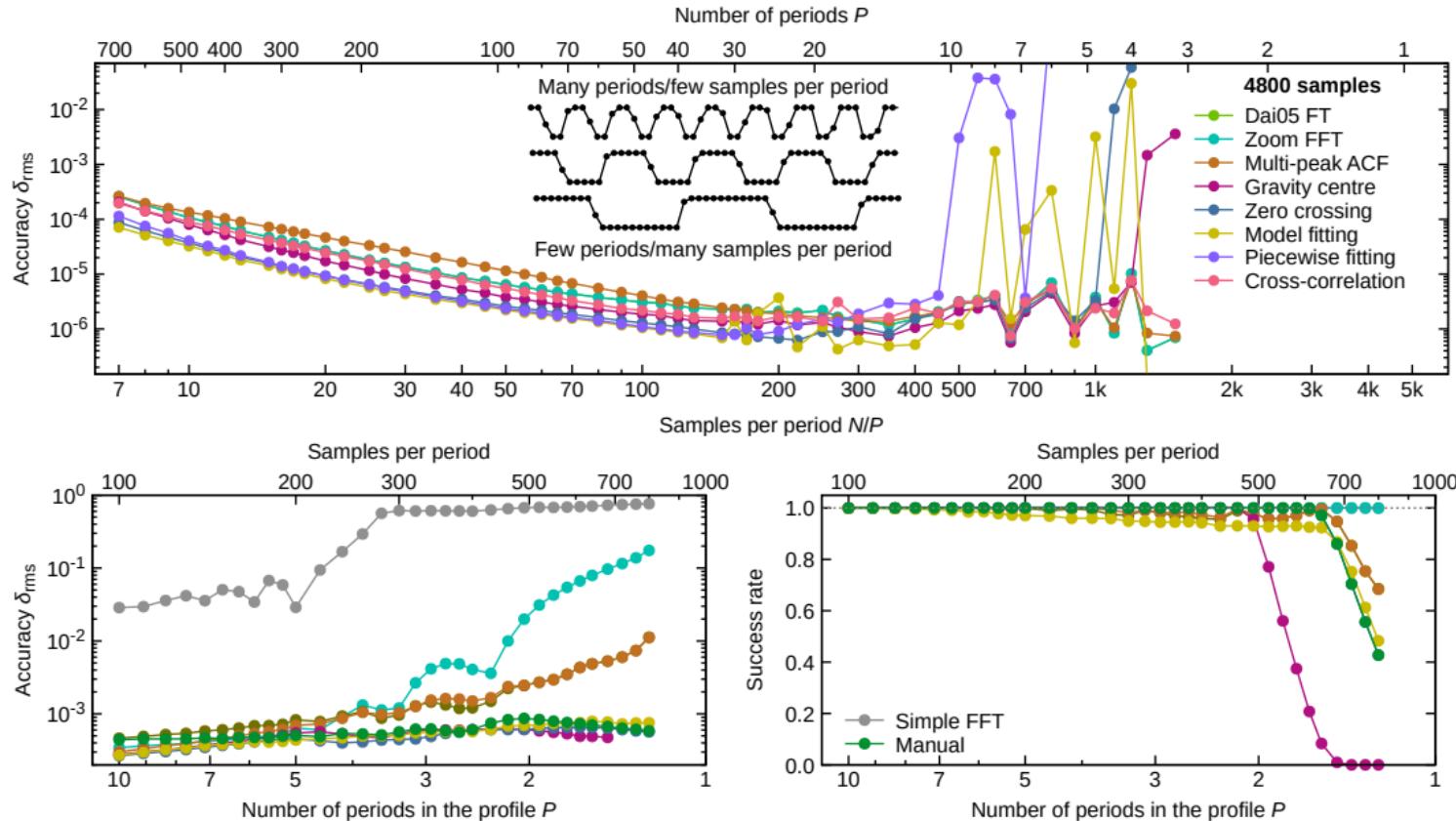
All good methods are similar – probably a theoretical limit



The extremes



The extremes



Steps on silicon

Secondary realisation of metre

Preparation of the 2018 update of the SI

Silicon lattice spacing

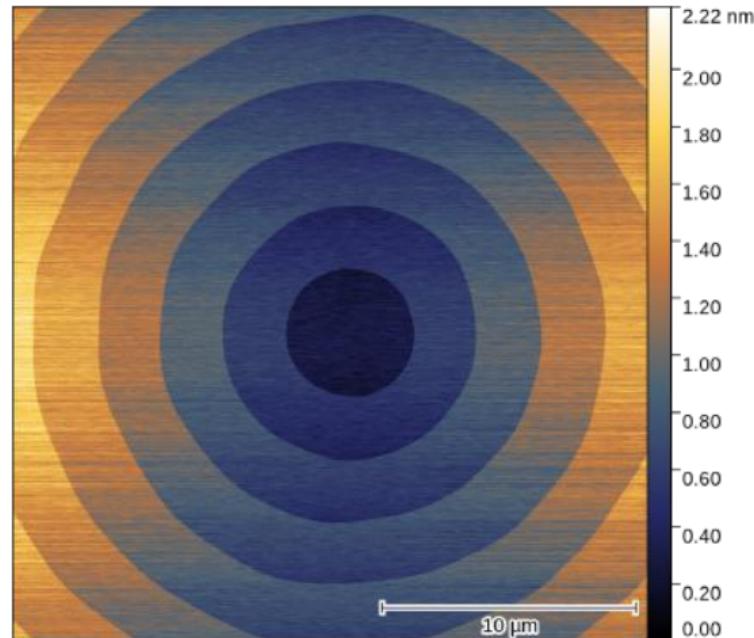
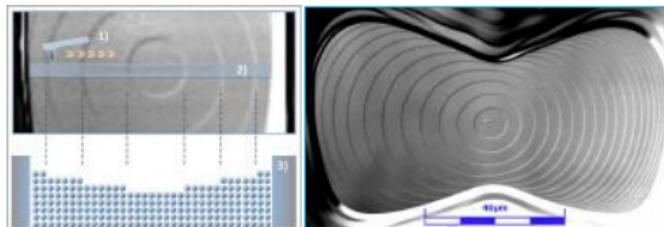
$$d_{220} = 192.015\,571\,6(32) \times 10^{-12} \text{ m}$$

Practical SPM standard

Mono atomic steps on Si (111) surface

Prepared using molecular beam epitaxy

$$d_{111} = 313.560\,115\,1(53) \times 10^{-12} \text{ m}$$



Consultative Committee for Length, Mise en pratique for the definition of the metre in the SI (2019)

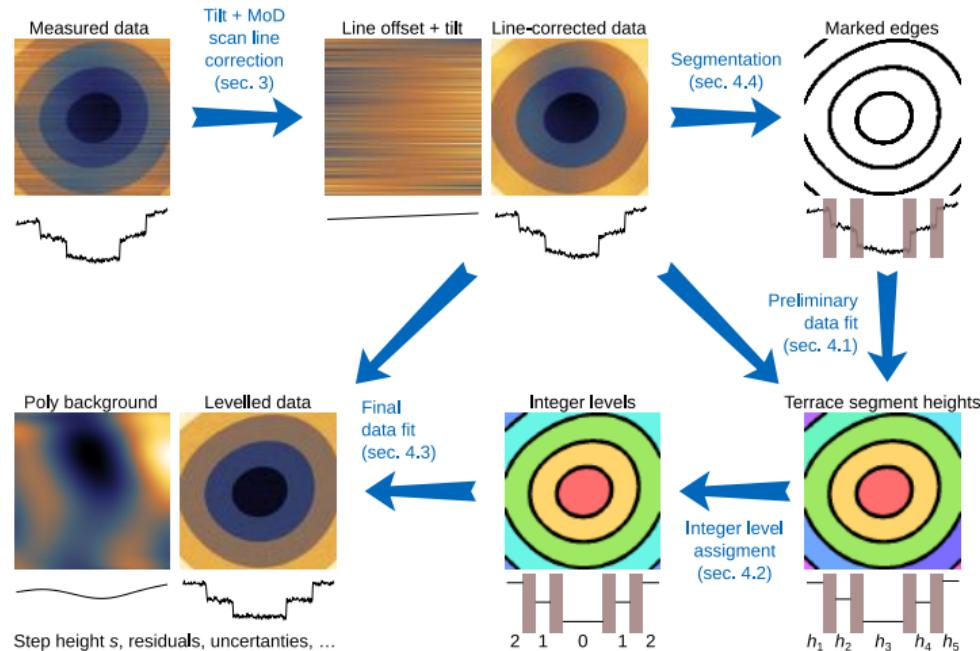
Tiesinga E., Mohr P.J., Newell N.B. and Taylor B.N., The 2018 CODATA Recommended Values of the Fundamental Physical Constants, (2019, Web Version 8.1)

Fissel A., Krugener J., and Osten H.J., Preparation of large step-free mesas on Si(111) by molecular beam epitaxy, *Phys. Status Solidi C* **9** (2012) 2050

Evaluation

Preprocessing

- ▶ line correction
- ▶ edge detection
- ▶ terrace marking
- ▶ connectivity graph



Fitting

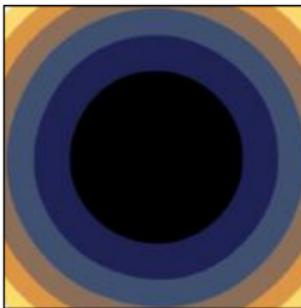
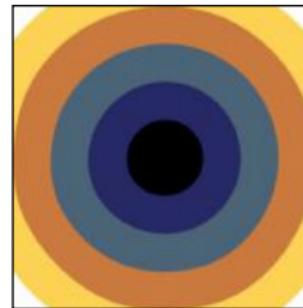
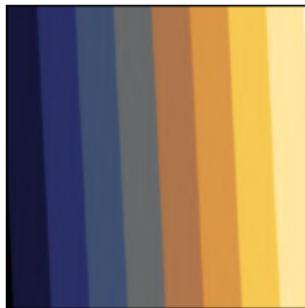
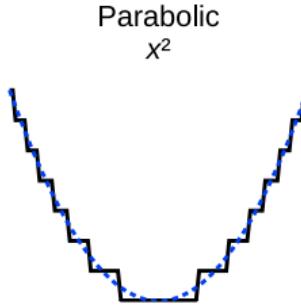
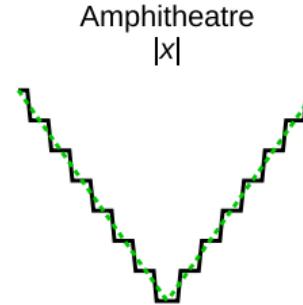
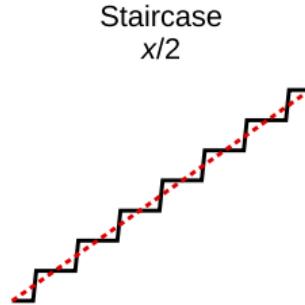
$$\text{Height}(x) = s \cdot \text{Level}(x) + \text{Poly}(x)$$

s – step height (fitted)

Level – levels (known integers)

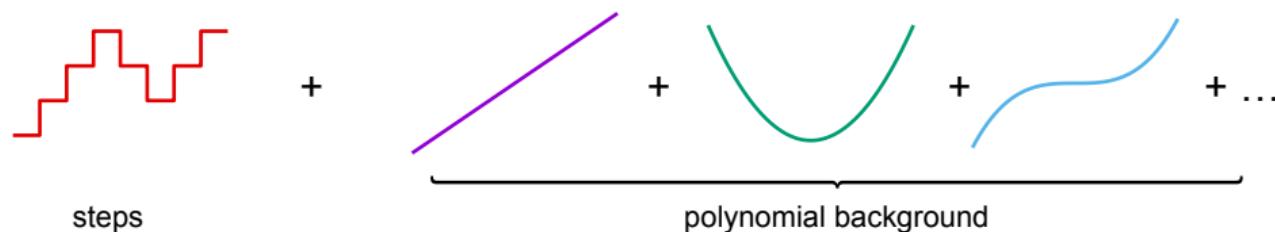
Poly – a polynomial (fitted)

Overall shape



Which overall shape is the best? worst?

Fitting the profile

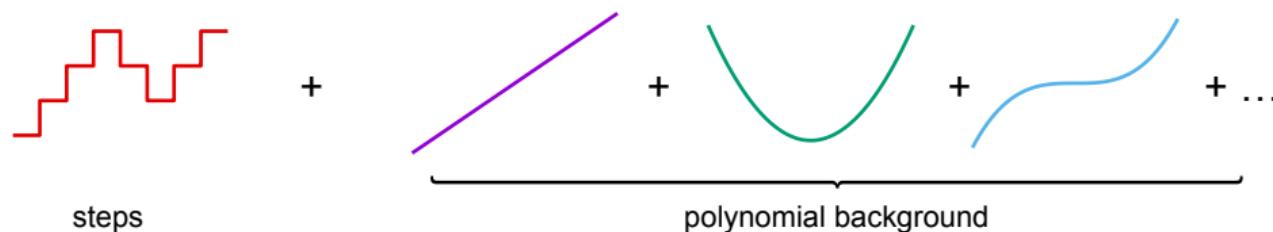


$$\text{Height}(x) = s \cdot \text{Level}(x) + \text{Poly}(x)$$

Distinct fitting functions – **Good**

Indistinguishable functions – **Bad**

Fitting the profile



$$\text{Height}(x) = s \cdot \text{Level}(x) + \text{Poly}(x)$$

Distinct fitting functions – **Good**

Indistinguishable functions – **Bad**

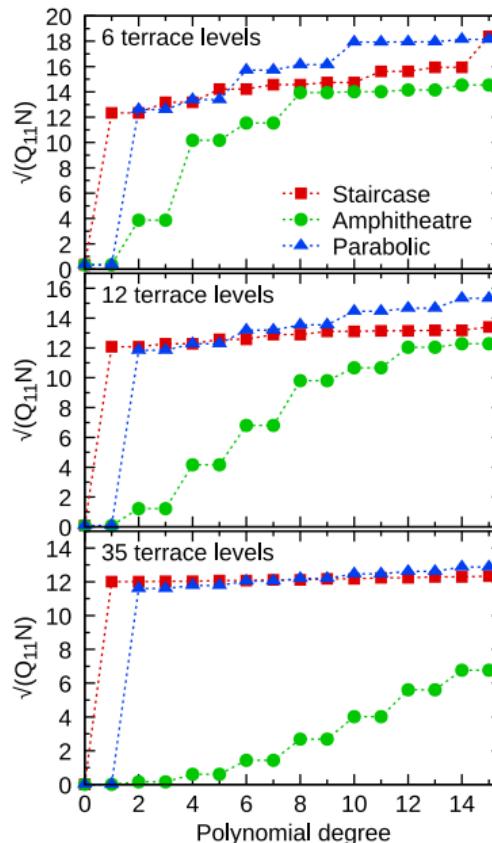
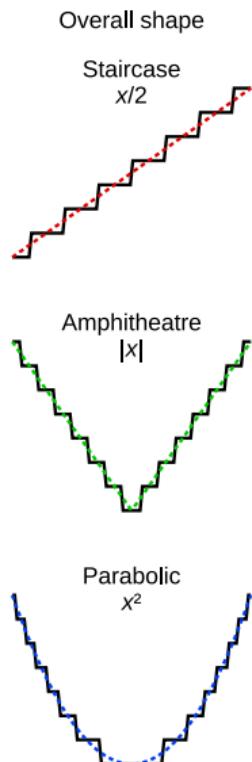
Staircase	– looks like x	– bad
Parabolic	– looks like x^2	– a bit less bad
Amphitheatre	– does not look like any polynomial	– good

$$\text{Step error } \Delta_s \propto \sqrt{Q_{11}} \cdot \text{Noise}$$

Cofactor matrix $\mathbf{Q} = (\text{Normal matrix})^{-1}$

- ▶ does not depend on noise
- ▶ computed from scalar products of basis fitting functions

The matrix



Assumptions

- ideal geometry
- no around-step exclusion
- amount of data $N \rightarrow \infty$

$\sqrt{Q_{11}N}$ plotted instead of $\sqrt{Q_{11}}$ for meaningful $N \rightarrow \infty$ limit

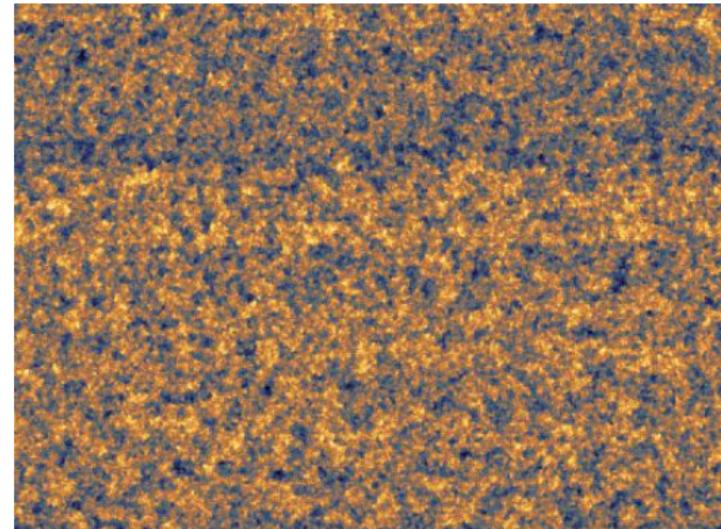
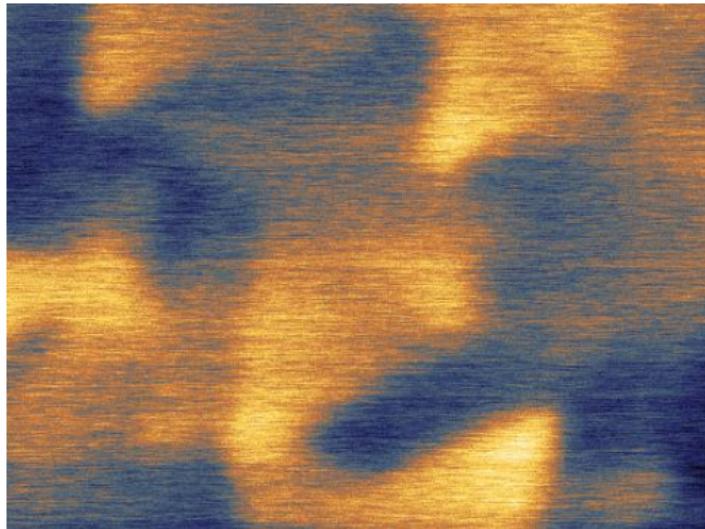
Few terraces

- poor measurement
- small difference

Many terraces

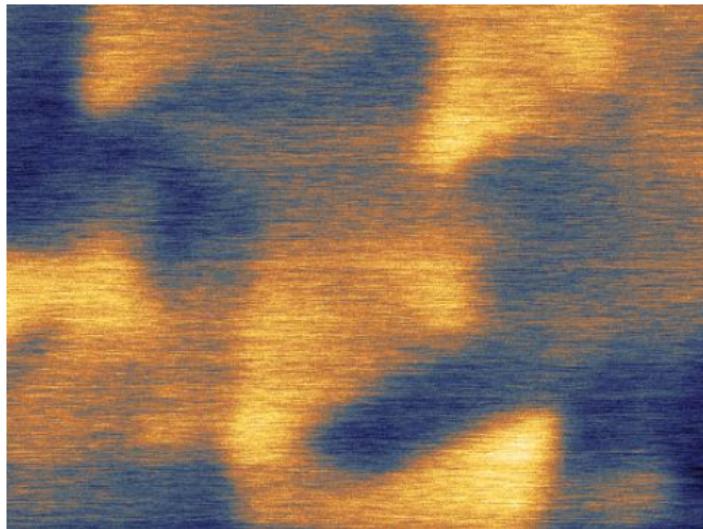
- good measurement
- huge difference

Which one is it?

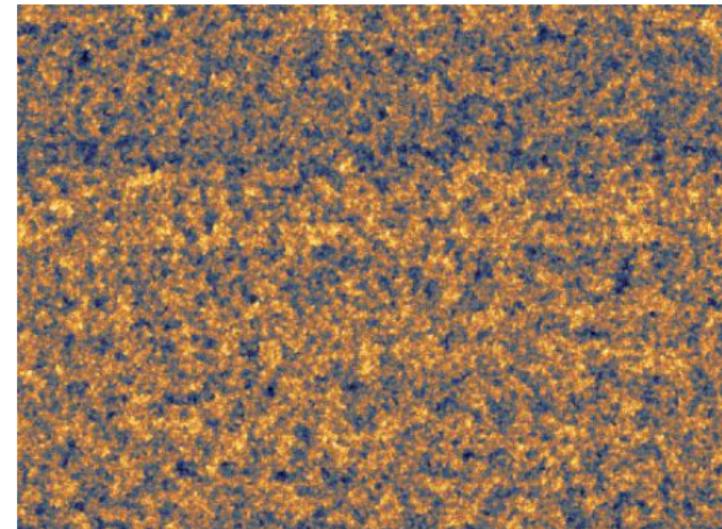


Which one is better for roughness? Left? Right? Neither?

Which one is it?



Pretty bad, $\gtrsim 30\%$ bias & poor representativeness.



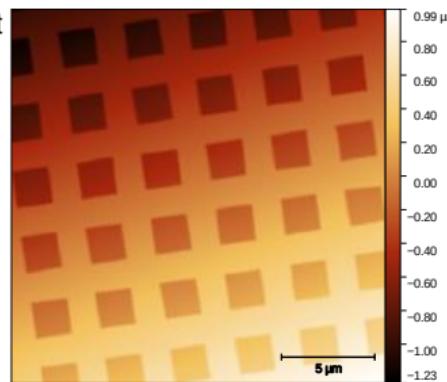
Probably good for evaluation.

Scan line must be long to avoid losing the lower spatial frequencies.

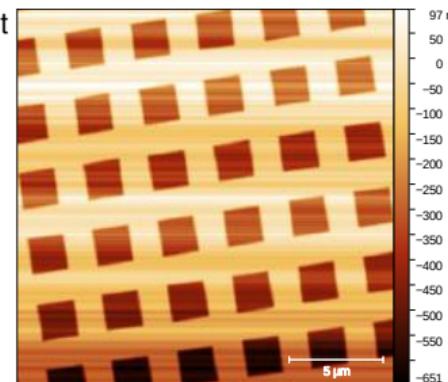
Governed by $\alpha = T/L$. Should be $\alpha \ll 1$.

In AFM usually incompatible with 'can nicely see features'.

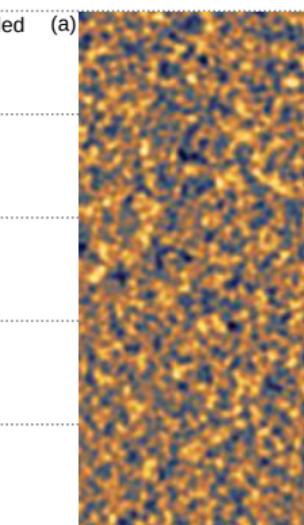
Sample tilt



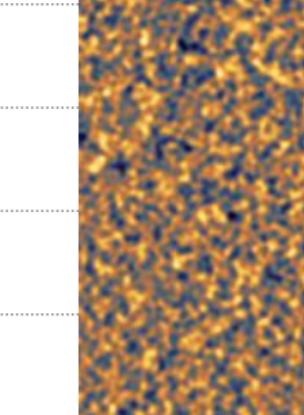
Scan line misalignment



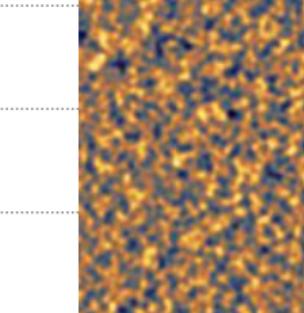
Not levelled



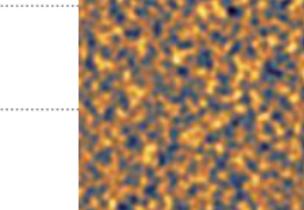
Poly 0



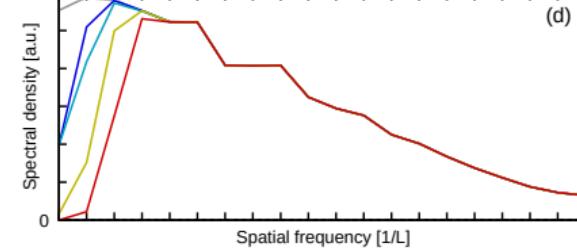
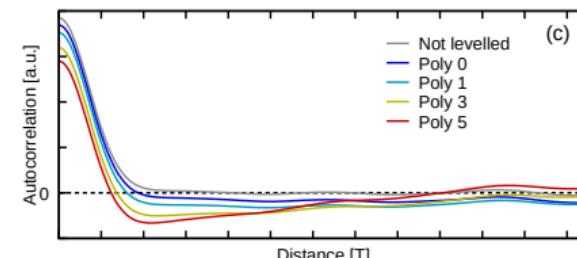
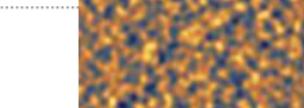
Poly 1

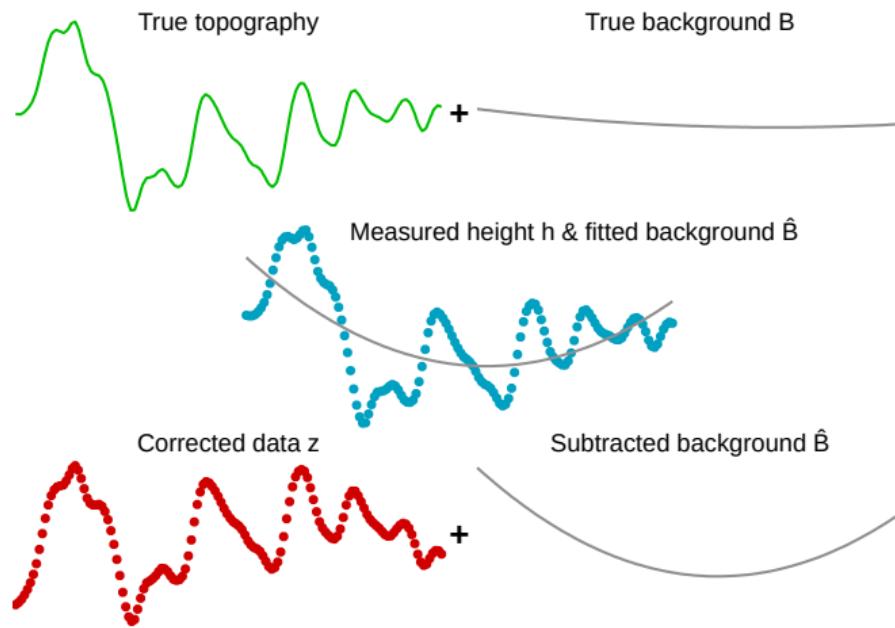


Poly 3



Poly 5





Bias of mean square roughness σ

$$E[\hat{\sigma}^2] = \sigma^2 - 2^D \int_0^1 C_n(t) G(tL) dt$$

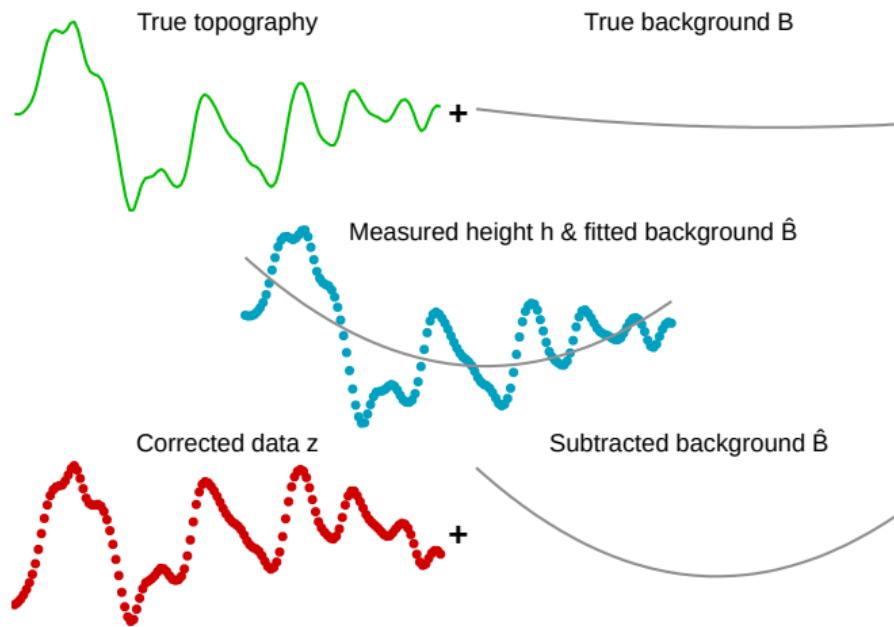
T – autocorrelation length

D – dimension (1, 2, ...)

G – autocorrelation function

C_n – ugly function

n – polynomial degree



Fit $G - RG$ instead of G to experimental data

$$G_{\text{Gauss}}^{\text{bias}}(\tau) \approx \sigma^2 \exp\left(-\frac{\tau^2}{T^2}\right) - \sqrt{\pi} n \sigma^2 \frac{T}{L} \left(1 + \frac{\tau}{L}\right) + n^2 \sigma^2 \frac{T^2}{L^2} \left(1 + \frac{2\tau}{L}\right)$$

Or invert $G = (1 - R)^{-1} \hat{G}$ (adventurous)

Bias of mean square roughness σ

$$E[\hat{\sigma}^2] = \sigma^2 - 2^D \int_0^1 C_n(t) G(tL) dt$$

T – autocorrelation length

D – dimension (1, 2, ...)

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C_n – ugly function

n – polynomial degree

Autocorrelation function to rescue

$$E[\hat{G}] = G - R_n G$$

G – autocorrelation function

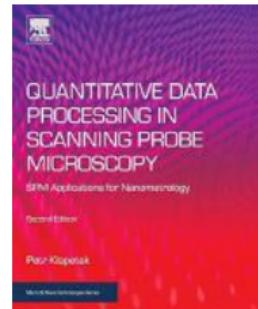
R_n – even uglier linear operator

G knows about its own bias!

Conclusions

- ▶ Measuring wrong is easy.
- ▶ Solid 'hardware' part $\not\Rightarrow$ useful data.
- ▶ *What do you measure?*
- ▶ Intuition often fails us.
- ▶ Simulate!

Almost everything is implemented in Gwyddion.



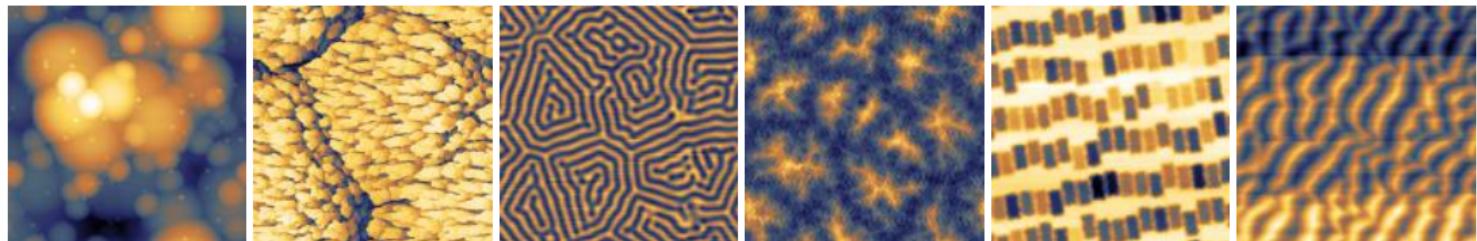
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Almost everything is implemented in Gwyddion.



Nothing you saw was real SPM data.



Nečas D., Klapetek P., Study of user influence in routine SPM data processing, *Measurement Science and Technology* **28** (2017) 034014

Nečas D., Klapetek P., Synthetic Data in Quantitative Scanning Probe Microscopy, *Nanomaterials* **11** (2021) 1746

Klapetek P., et al., Quantitative Data Processing in Scanning Probe Microscopy, 2nd edition, Elsevier (2018)