An Investigation of the Disorder Potential of QPC via Scanning Gate Microscopy and Machine Learning

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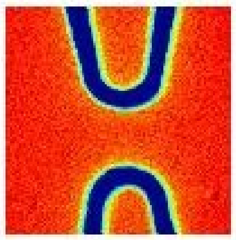
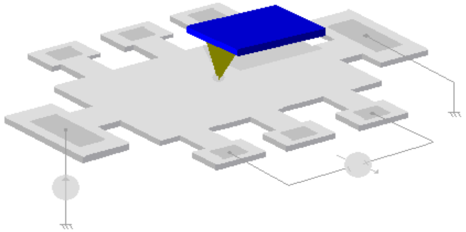
APS March Meeting 2023 – Session F52, Tue. 10 am

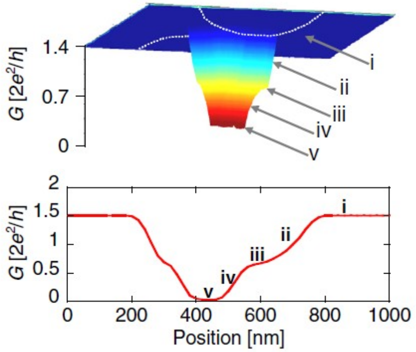
Structure of the Talk

- Quantum Point Contacts (QPC)
- Scanning Gate Microscopy (SGM)
- Device Fabrication
- Characterization
    - Transmission
    - Shubnikov-de Haas
    - SGM
- Machine Learning
    - Convolutional Neural Nets
    - Cellular Neural Nets
- Swarming Approach
    - Roughness
    - Correlations

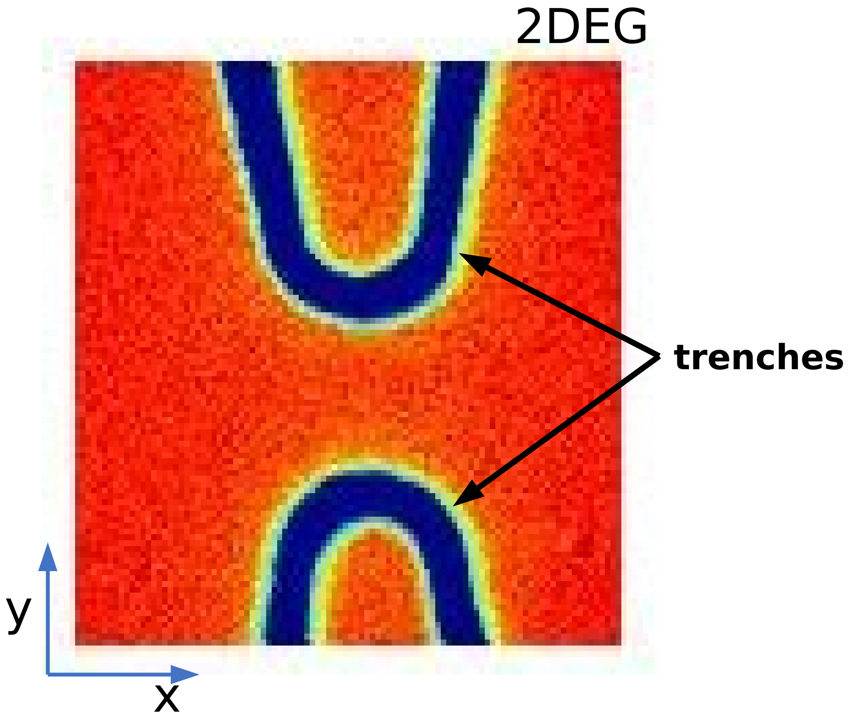
- Conclusions

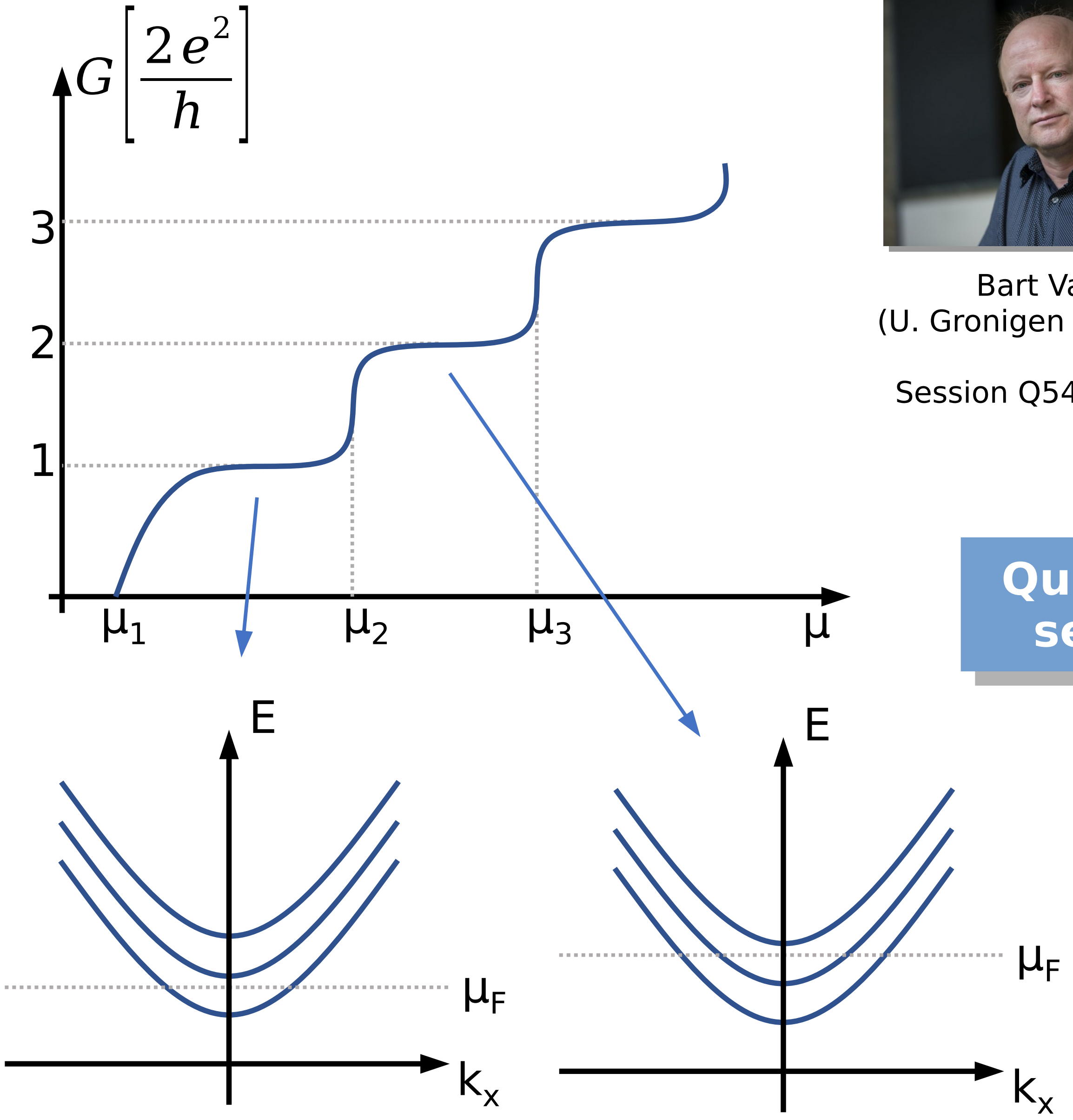






Quantum Point Contacts

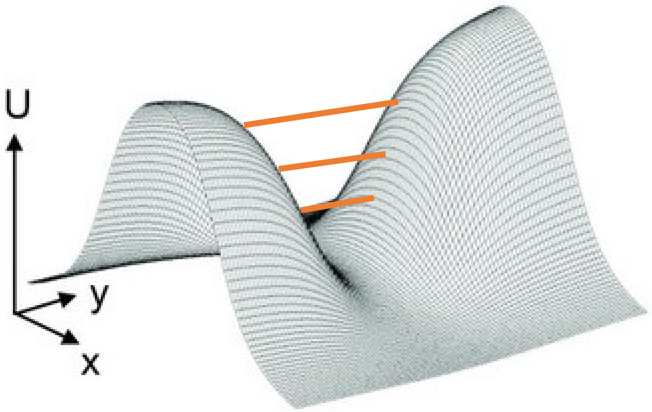




Bart Van Wees
(U. Gronigen – Netherlands)

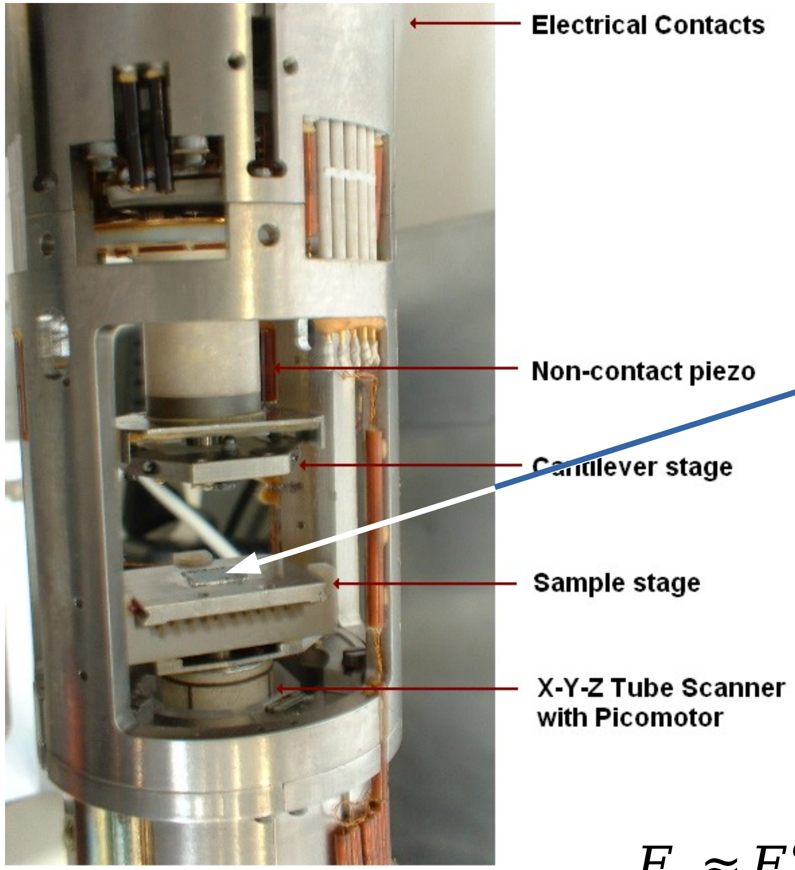
Session Q54 – Wed. 3 pm

Quantum sensor

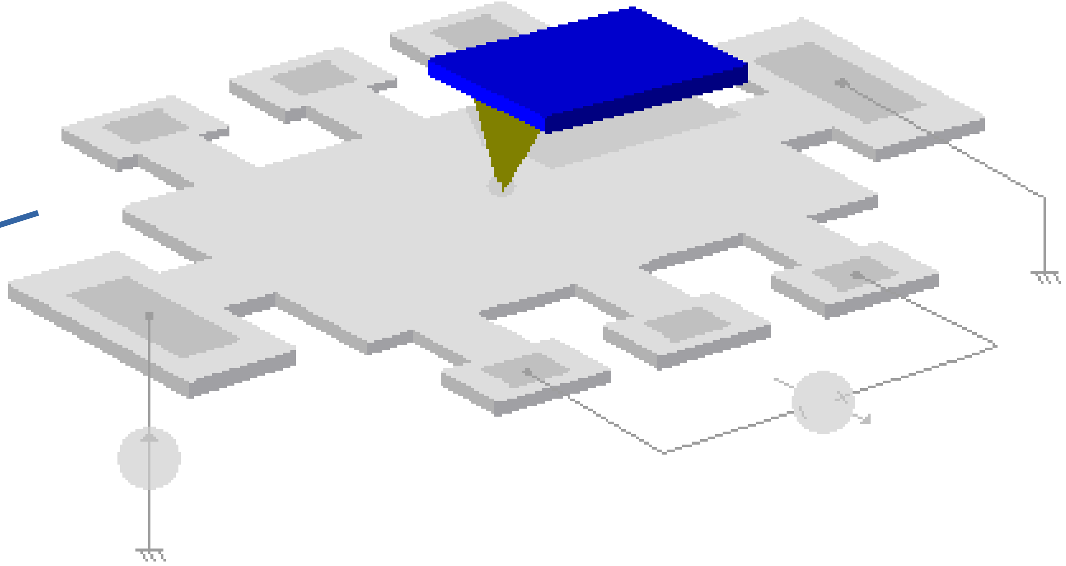


B.J. van Wees et al. "Quantized conductance of point contacts in a two-dimensional electron gas". *Phys. Rev. Let.* **60**-9 (1988) 848–850.

Scanning Gate Microscopy



$$V = V_0 \delta(\boldsymbol{r} - \boldsymbol{r_0})$$



$$E_n \approx E_n^o + \langle n | V | n \rangle$$

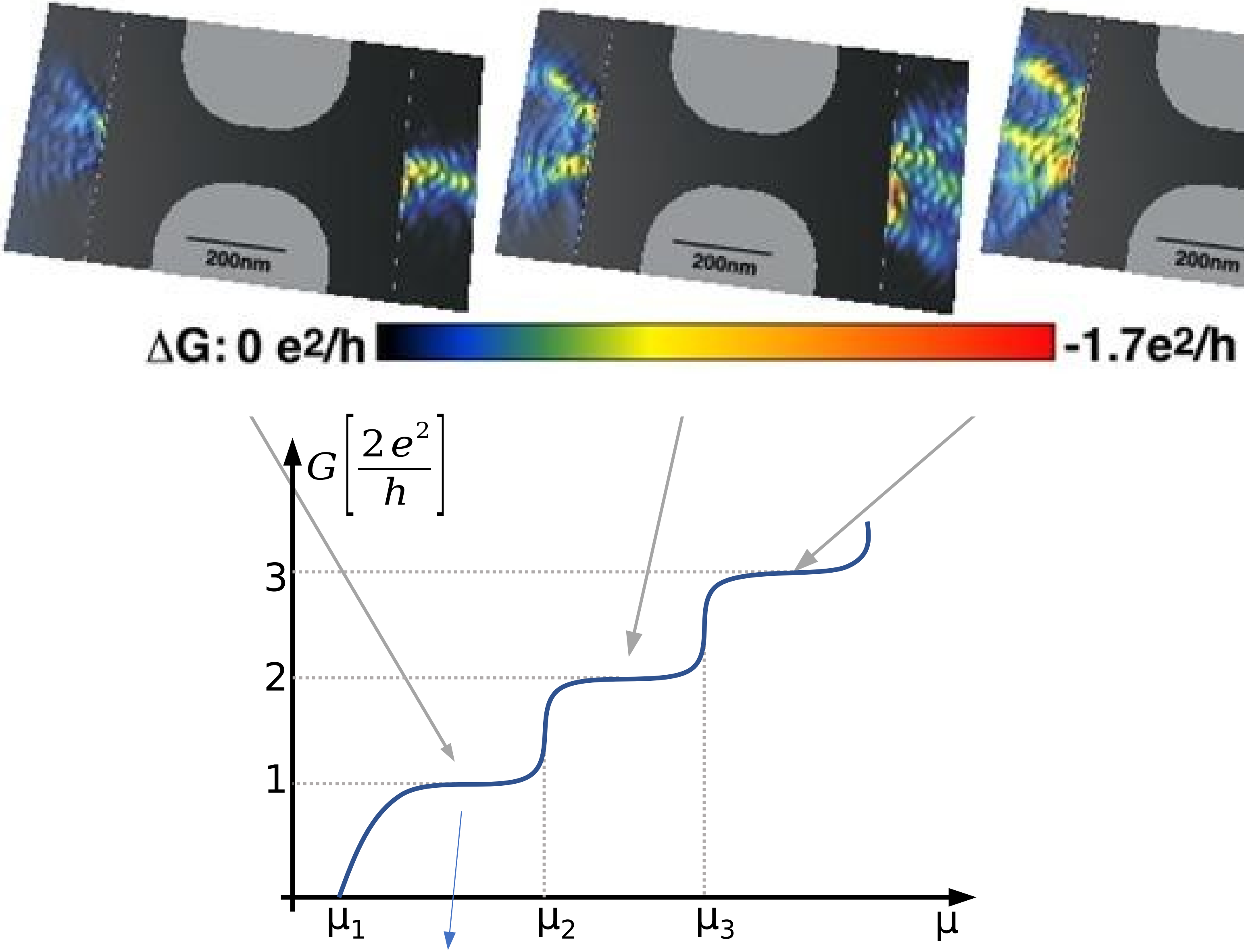
$$\Delta E_n \approx V_0 |\varphi_n(\boldsymbol{r_0})|^2$$

$$\Delta G(\boldsymbol{r_0}) \approx \frac{\partial G}{\partial E_F} \Delta E_n$$

$$\Delta G(\boldsymbol{r_0}) \approx V_0 \frac{\partial G}{\partial E_F} |\varphi_n(\boldsymbol{r_n})|^2$$

Shifts proportional to LDOS

Electron Flow



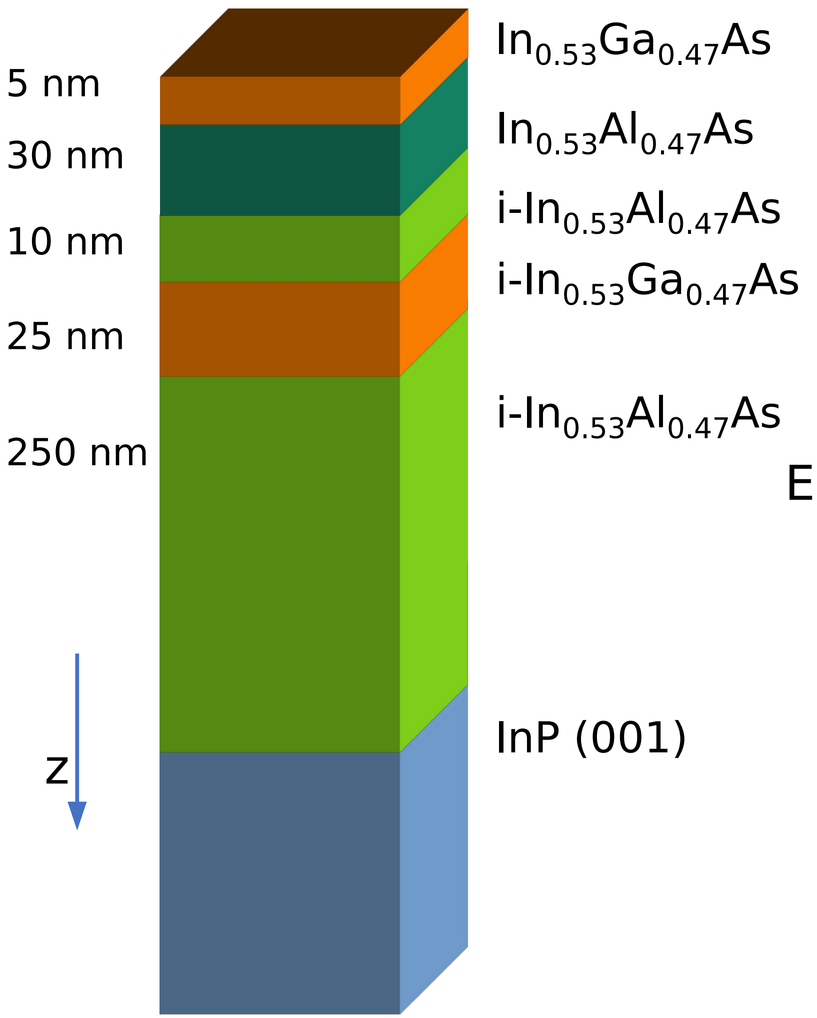
R. Westervelt
(Harvard)

Session N29
Wed. 11:30 am

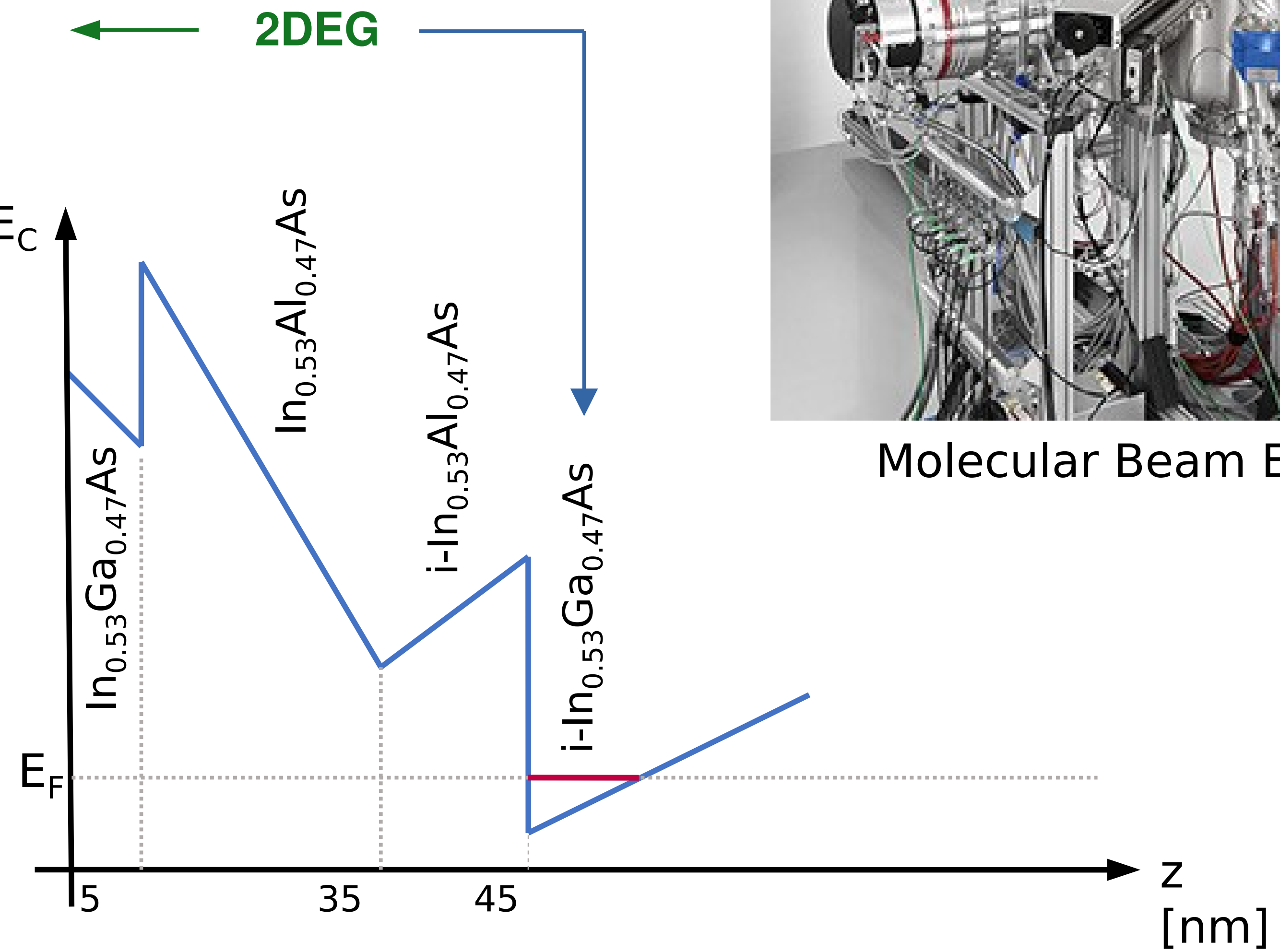
M. A. Topinka, B. J. LeRoy, S. E. J. Shaw, E. J. Heller, R. M. Westervelt, K. D. Maranowski, A. C. Gossard, “Imaging Coherent Electron Flow from a Quantum Point Contact”, *Science* **289** (2000) 2323.

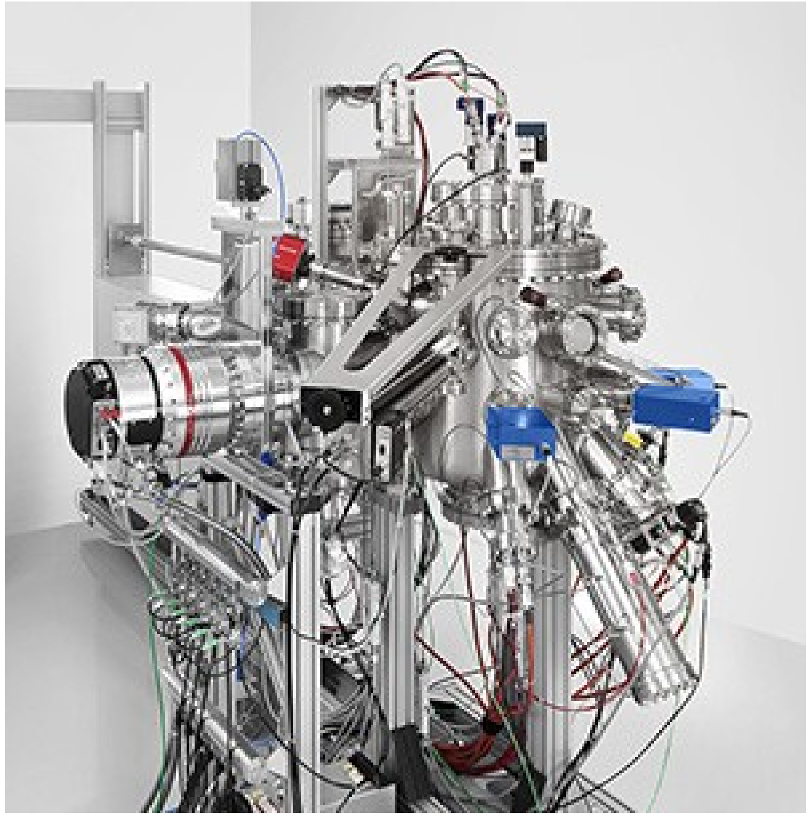
Device Fabrication

Heterostructure



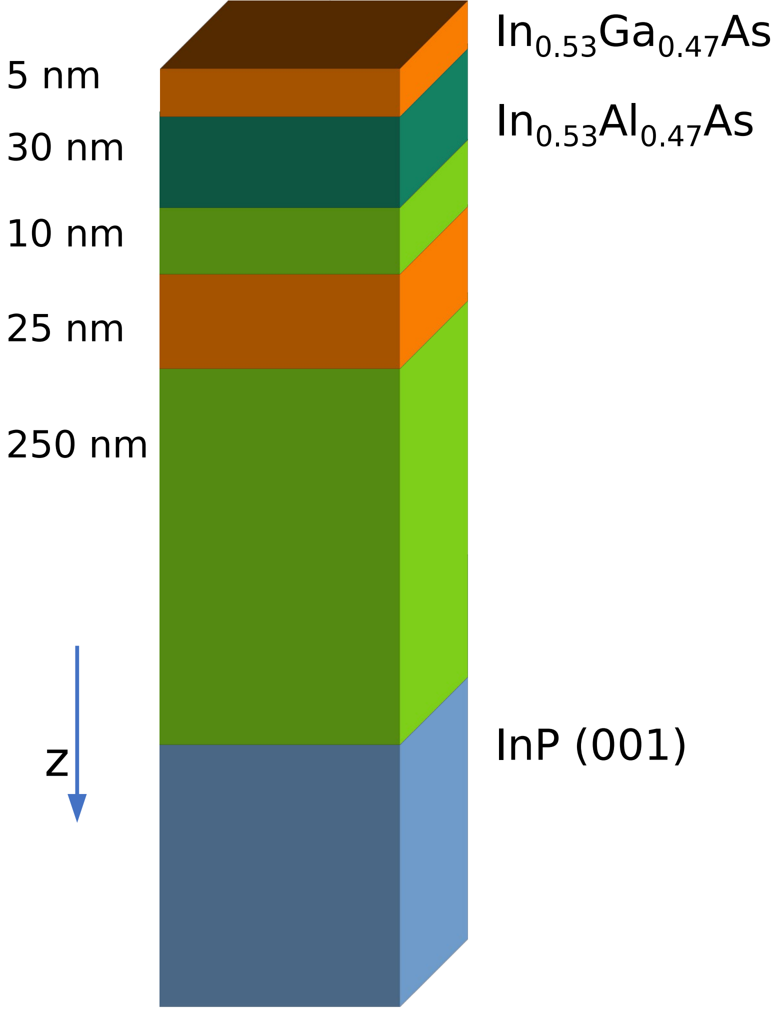
MBE-grown quantum well



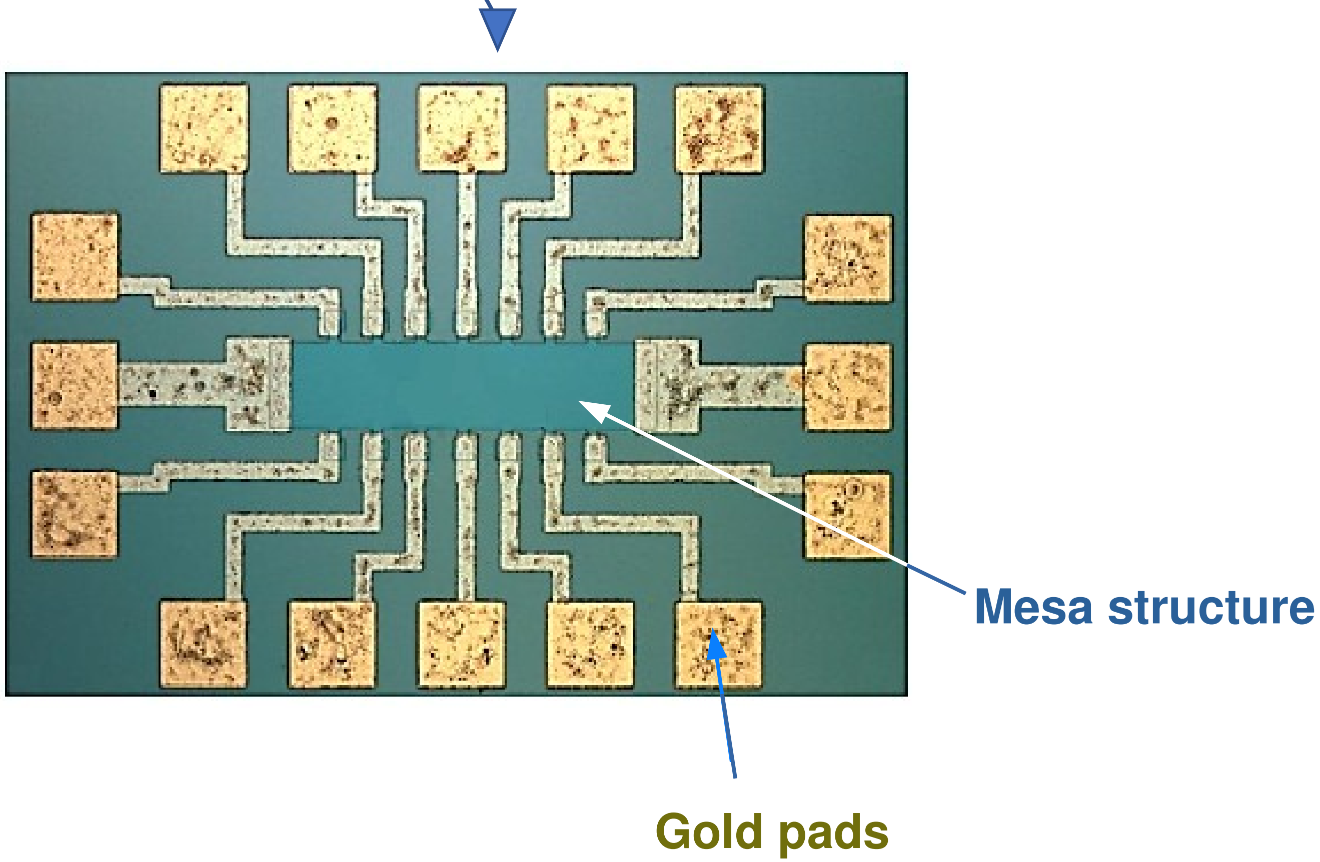


Molecular Beam Epitaxy

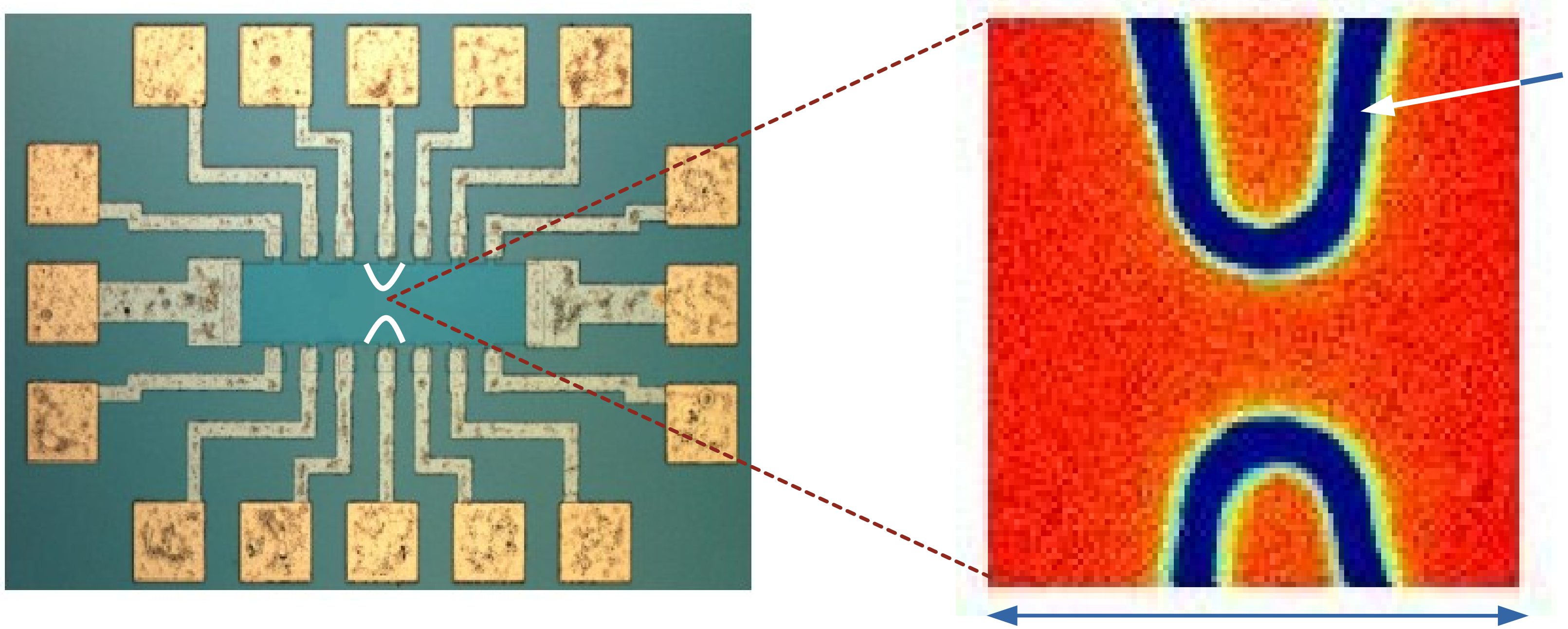
Hall bar



MBE-grown quantum well



EBL-Defined QPC

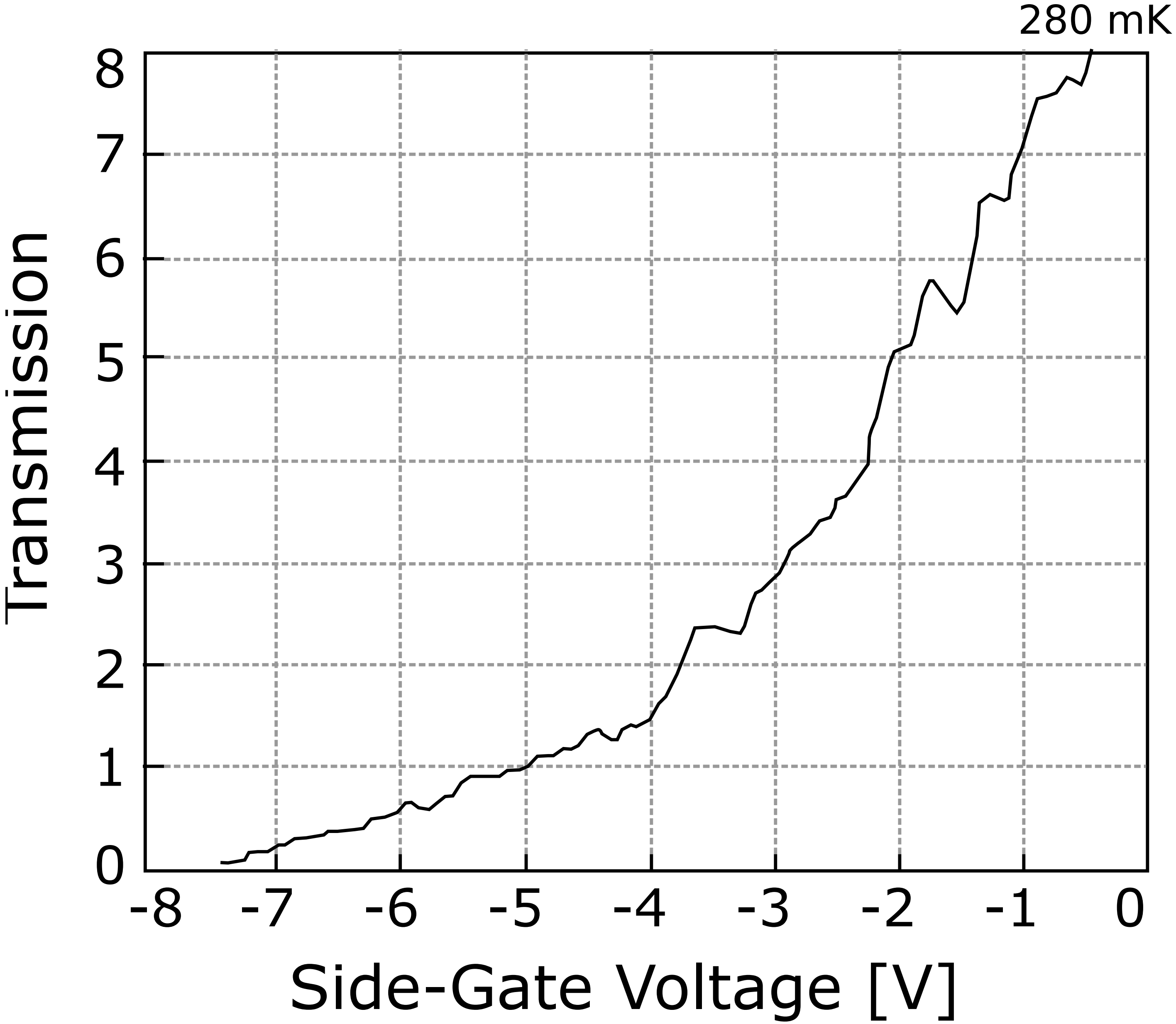


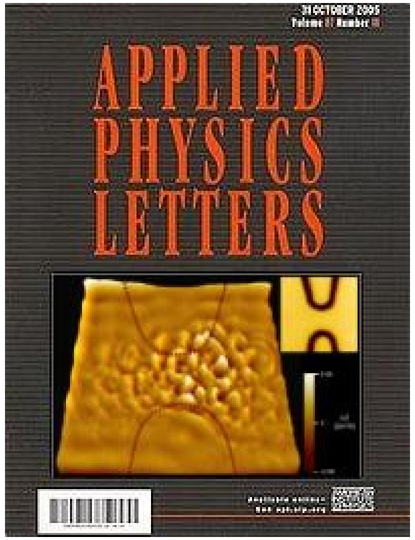
Electron beam lithography

Characterization

- Shubnikov de-Haas
- Quantum Hall
- Quantum Chaos

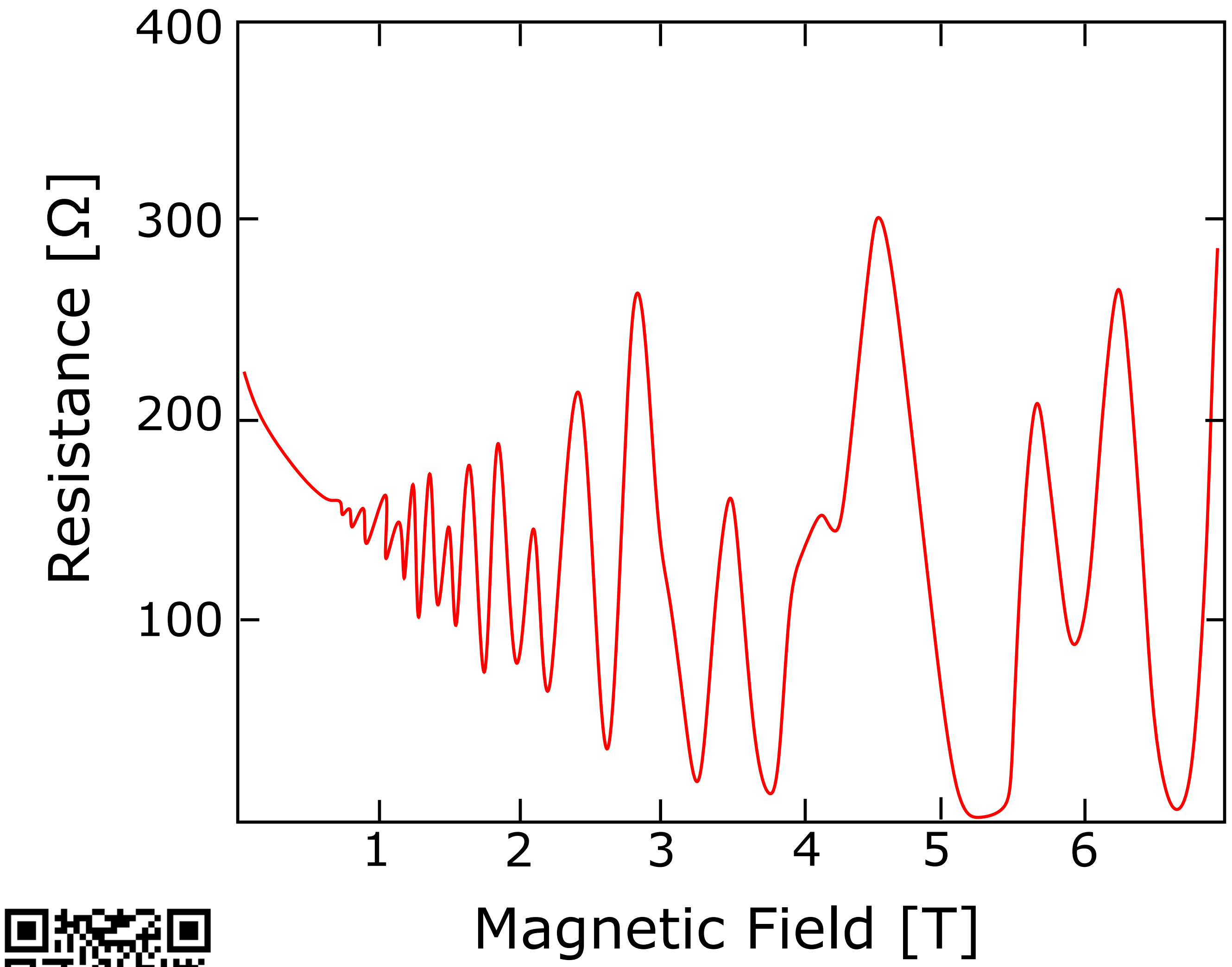
Transmission



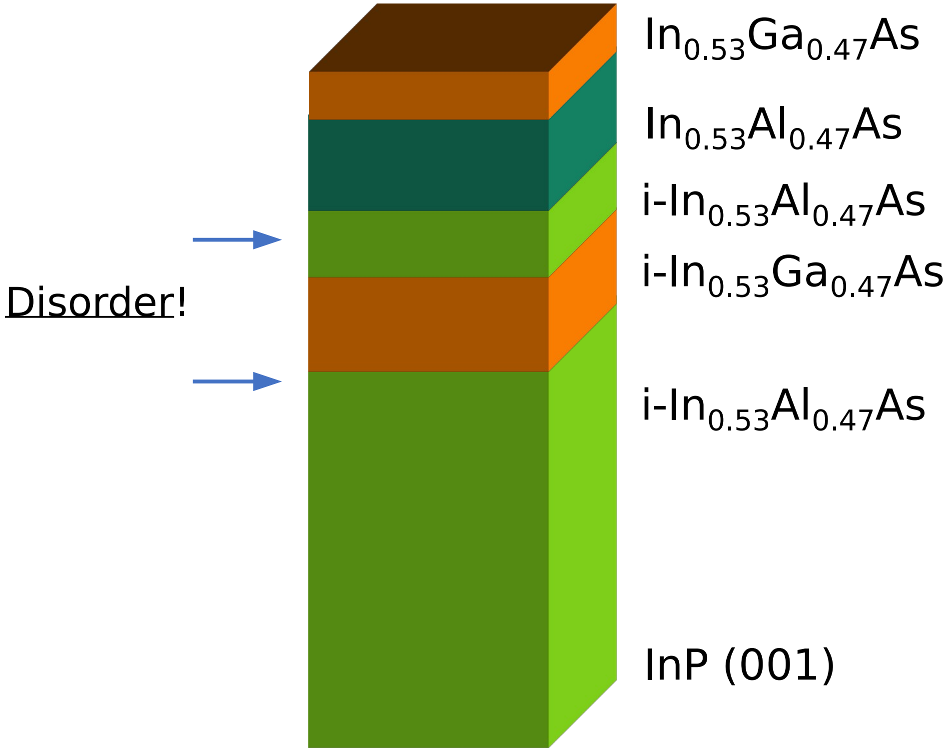


C. R. da Cunha, et al.
Imaging of quantum interference patterns within a quantum point contact
Appl. Phys. Lett. **89-24** (2006) 242109.

Shubnikov-de Haas



n = 7.2 × 10^{11} cm^{-2}, 2.1 × $10^{11}$$cm^{-2}$
μ = 7.4 × 10^{4} cm^{2}/V.s
l = 1.2 μm



$In_{0.53}Ga_{0.47}As$

$In_{0.53}Al_{0.47}As$

i-$In_{0.53}Al_{0.47}As$

i-$In_{0.53}Ga_{0.47}As$

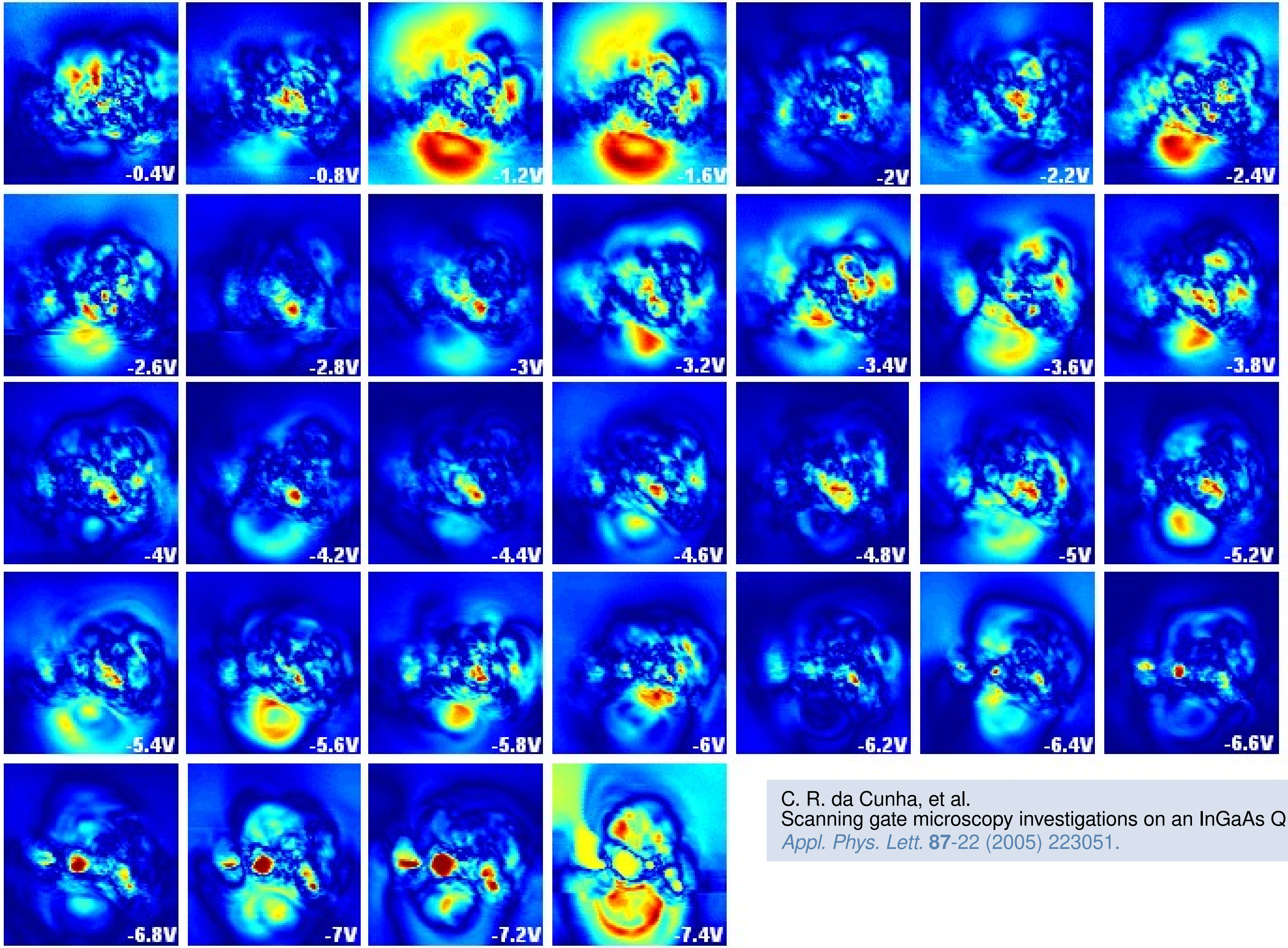
i-$In_{0.53}Al_{0.47}As$

InP (001)

Disorder!

C. R. da Cunha, et al.
Scanning gate imaging of a disordered quantum point contact
J. Phys. Cond. Matt. **26-19** (2014) 193202.

Scanning Gate Microscopy



C. R. da Cunha, et al.
Scanning gate microscopy investigations on an InGaAs QPC
Appl. Phys. Lett. **87**-22 (2005) 223051.

Too Many Assumptions…

IF {

1. The perturbation is sufficiently small;
2. The induced potential is delta-shaped
3. Wave function is given solely by states at the Fermi energy;
4. The conductance does not change much with Fermi energy (plateau);

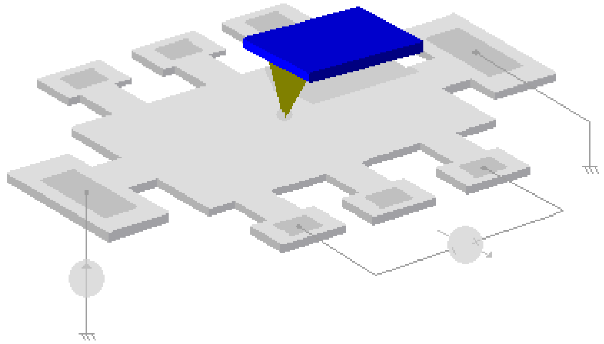
}

Then {

Changes in conductance (ΔG) ∝ local density of states (LDOS).

$$\Delta G\left(\boldsymbol{r_0}\right) \approx V_0 \frac{\partial G}{\partial E_F} \left|\varphi_n\left(\boldsymbol{r_n}\right)\right|^2$$

}



But…

Clouds are not spheres, mountains are not cones, coastlines are not circles, barks are not smooth, lighting does not travel in a straight line,…

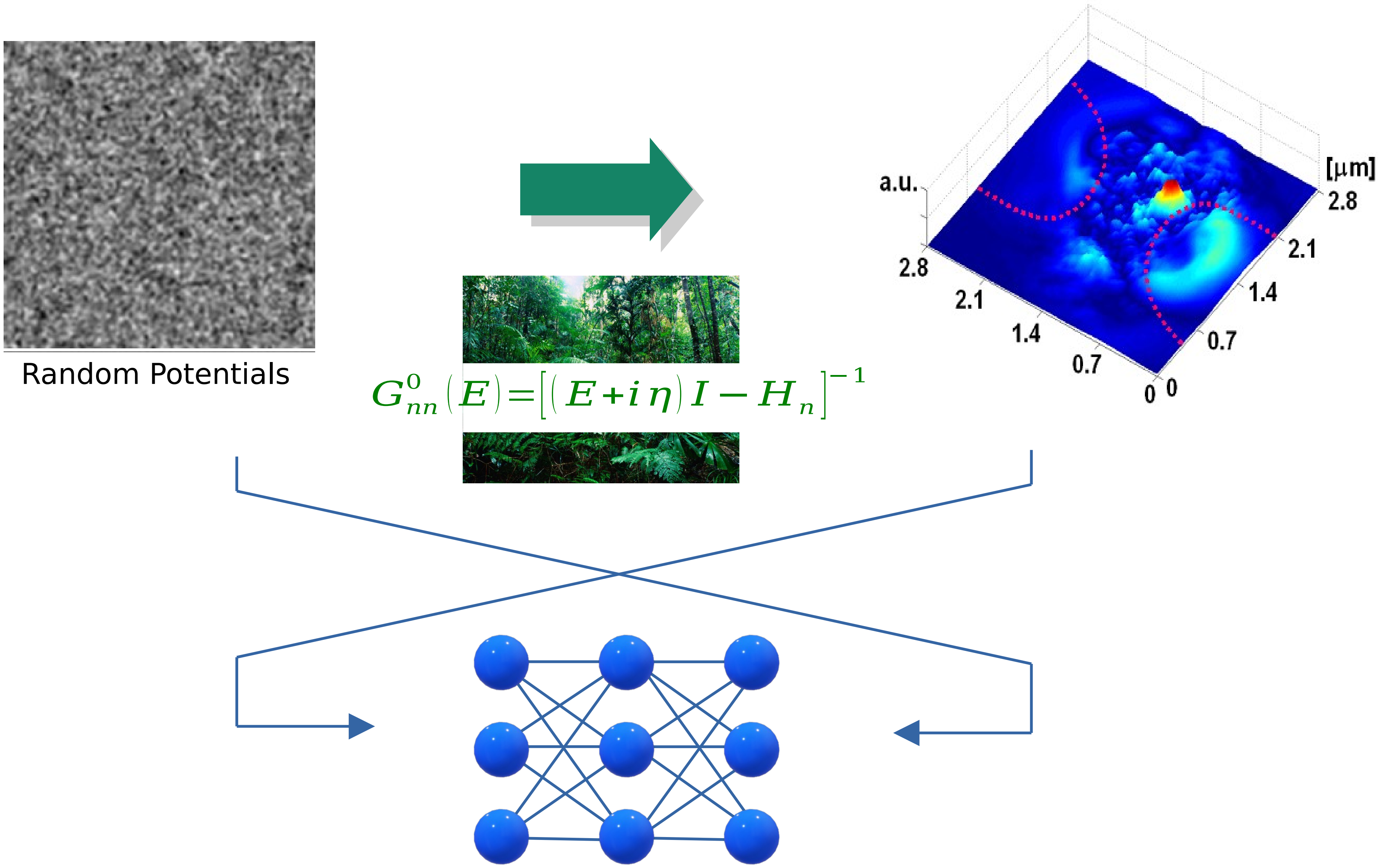
B. Mandelbrot
(1924 – 2010)

… ΔG is not small, the tip potential is not delta-shaped, not all states are in the Fermi level, and the conductance changes considerably with the Fermi level.

Machine Learning

- Shubnikov de-Haas
- Quantum Hall
- Quantum Chaos

Inverse Problem

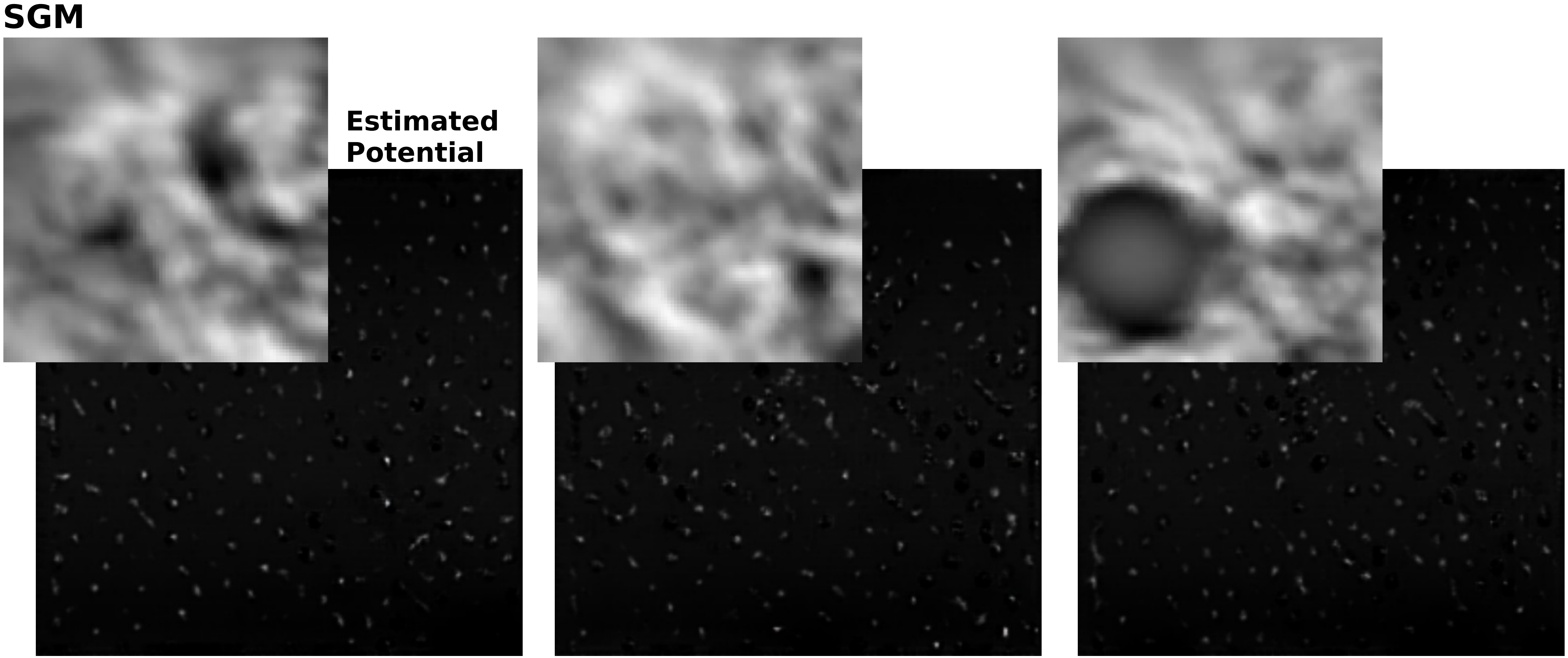


Random Potentials

$$G^{0}_{nn}(E)=\left[(E+i\eta)I-H_{n}\right]^{-1}$$

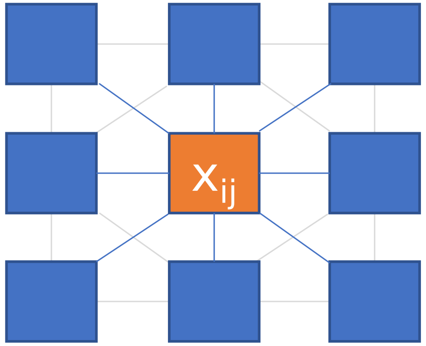
Nonlinear array of elements

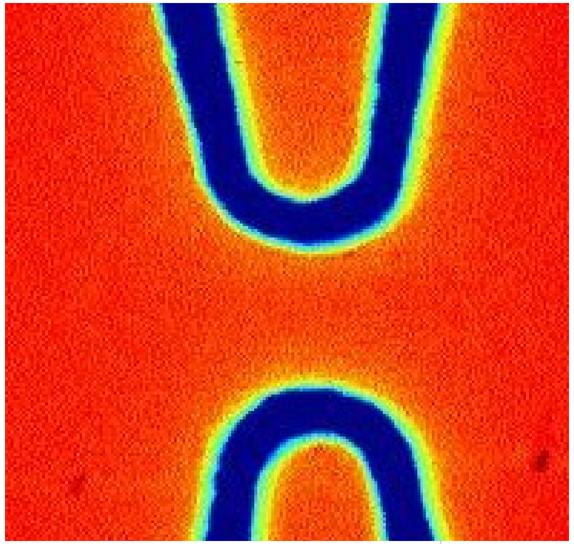
Results



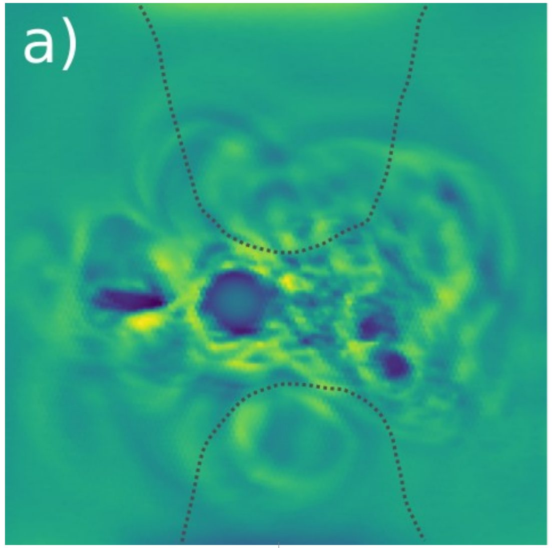
Slow processing limits the number of training samples!

Cellular Neural Network





Theoretical Potential



Theoretical LDOS

10k pairs with random Gaussian noise.

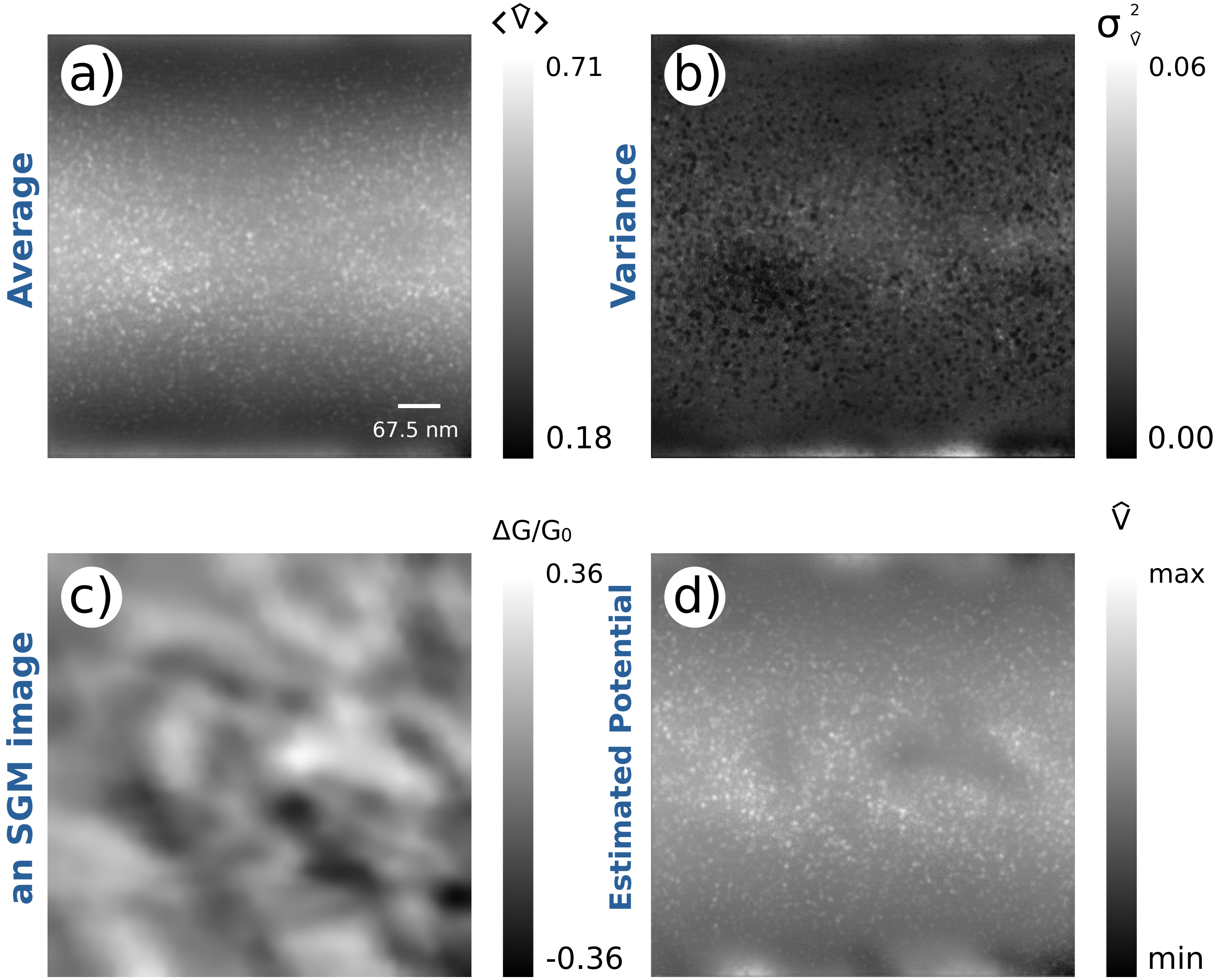
$$\frac{dX_{i,j}(t)}{dt} = -X_{i,j}(t) + \sum_{k,l} A_{i,j,k,l} Y_{k,l}(t) + \sum_{k,l} B_{i,j,k,l} U_{k,l}(t) + Z$$

state

output

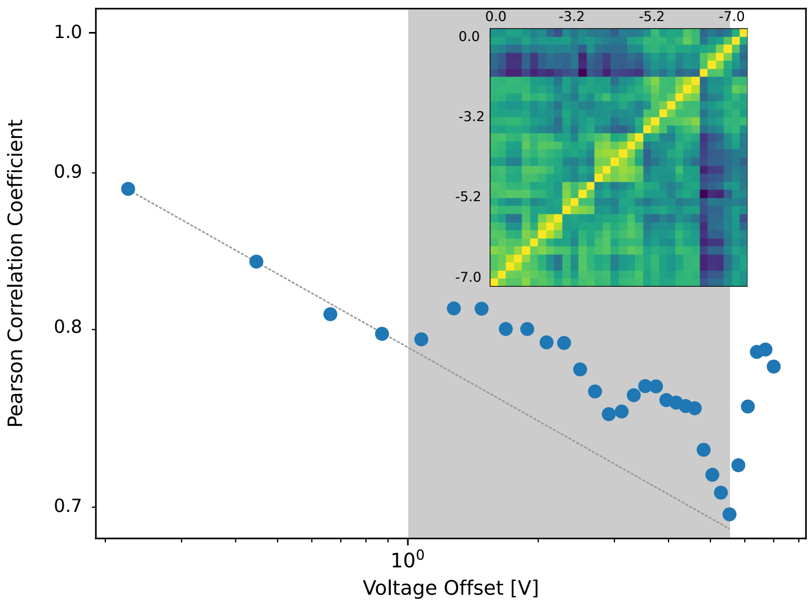
input

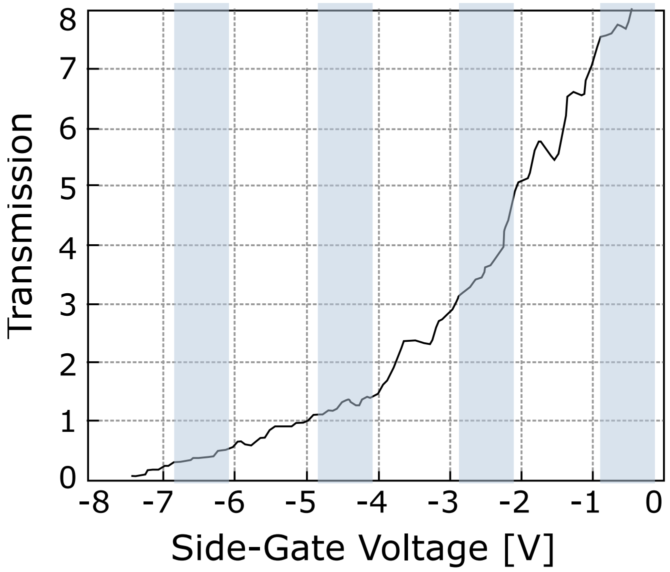
Results

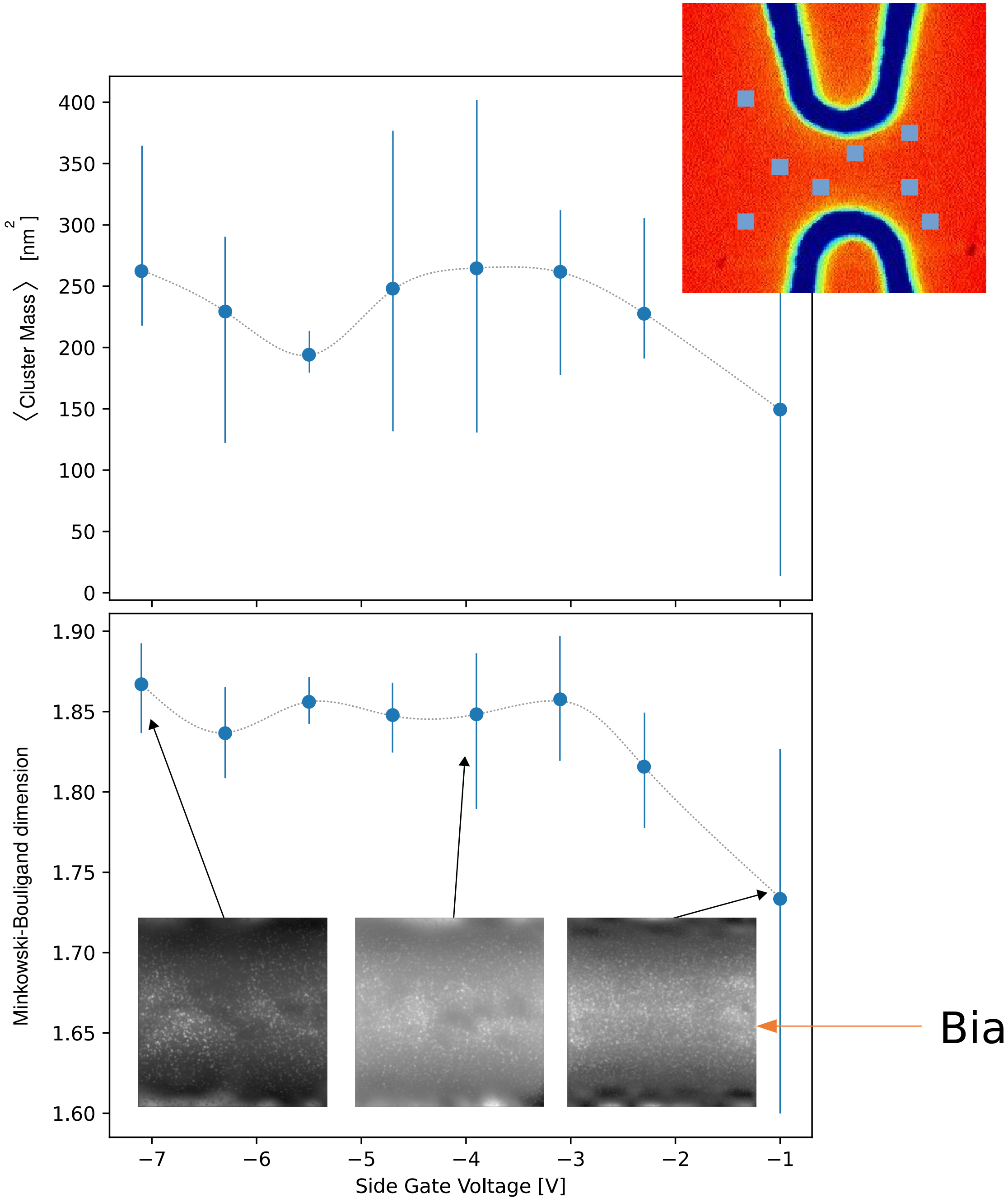


C. R. da Cunha, et al. A method for finding the background potential of quantum devices from scanning gate microscopy data using machine learning, *Mach. Learn. Sci. Tech.* **3** (2022) 025013.

Statistics

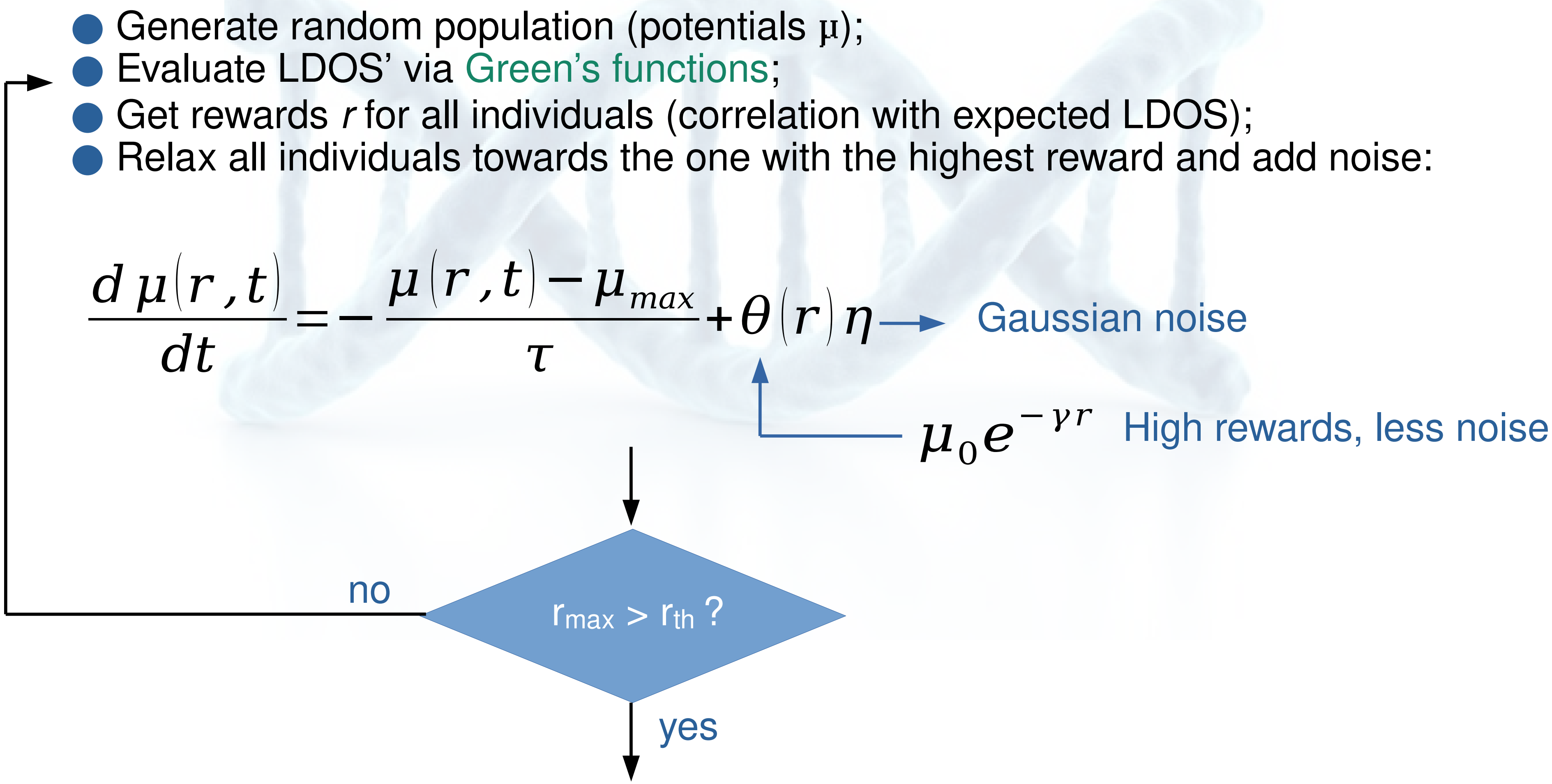






Biased!

Swarming Approach



- Generate random population (potentials μ);
- Evaluate LDOS' via Green's functions;
- Get rewards *r* for all individuals (correlation with expected LDOS);
- Relax all individuals towards the one with the highest reward and add noise:

$$\frac{d\mu(r,t)}{dt} = -\frac{\mu(r,t)-\mu_{max}}{\tau} + \theta(r)\eta$$

Gaussian noise

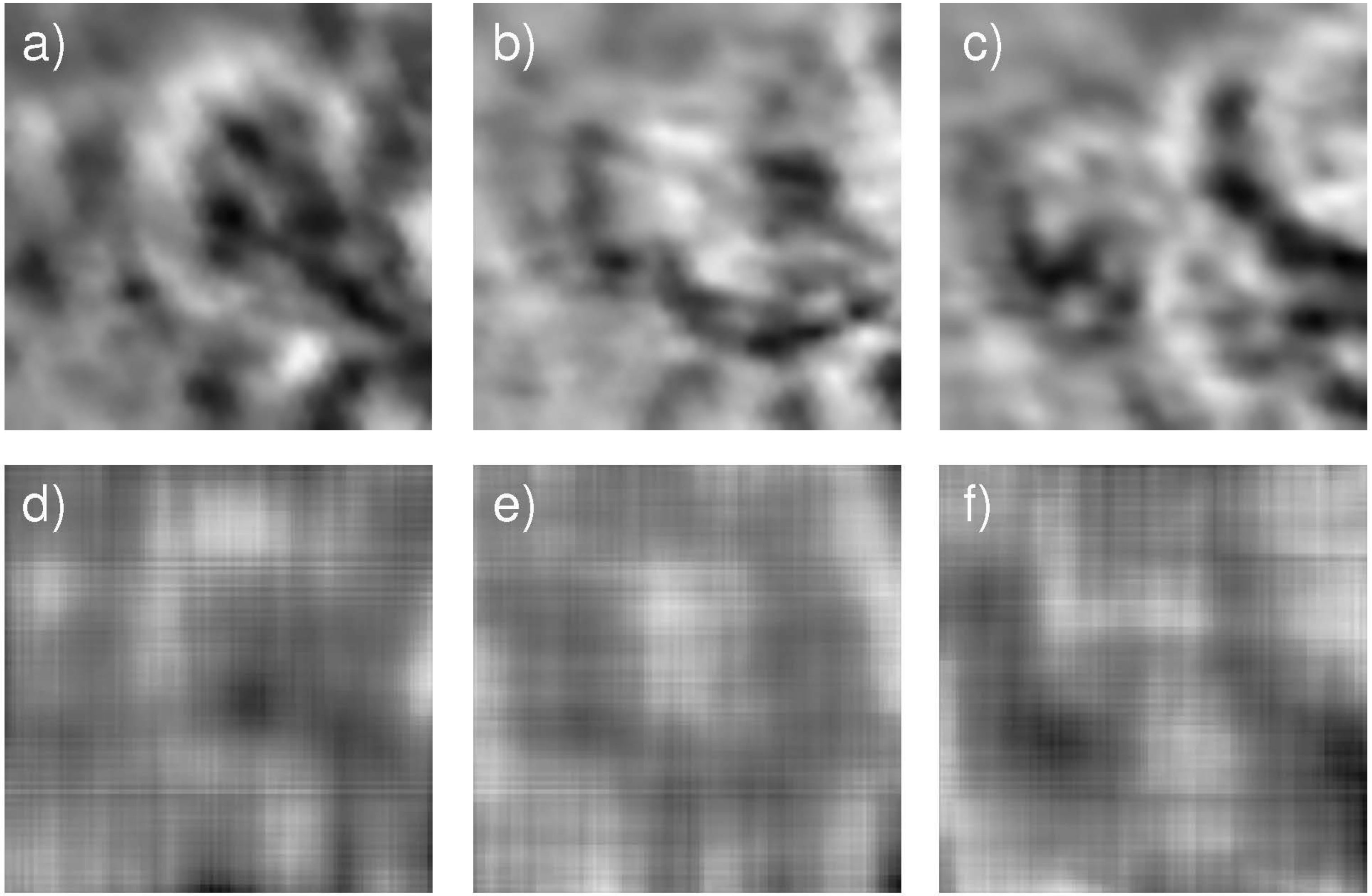
$\mu_0 e^{-\gamma r}$ High rewards, less noise

$r_{max} > r_{th}$?

no

yes

72 % Correlated SGM

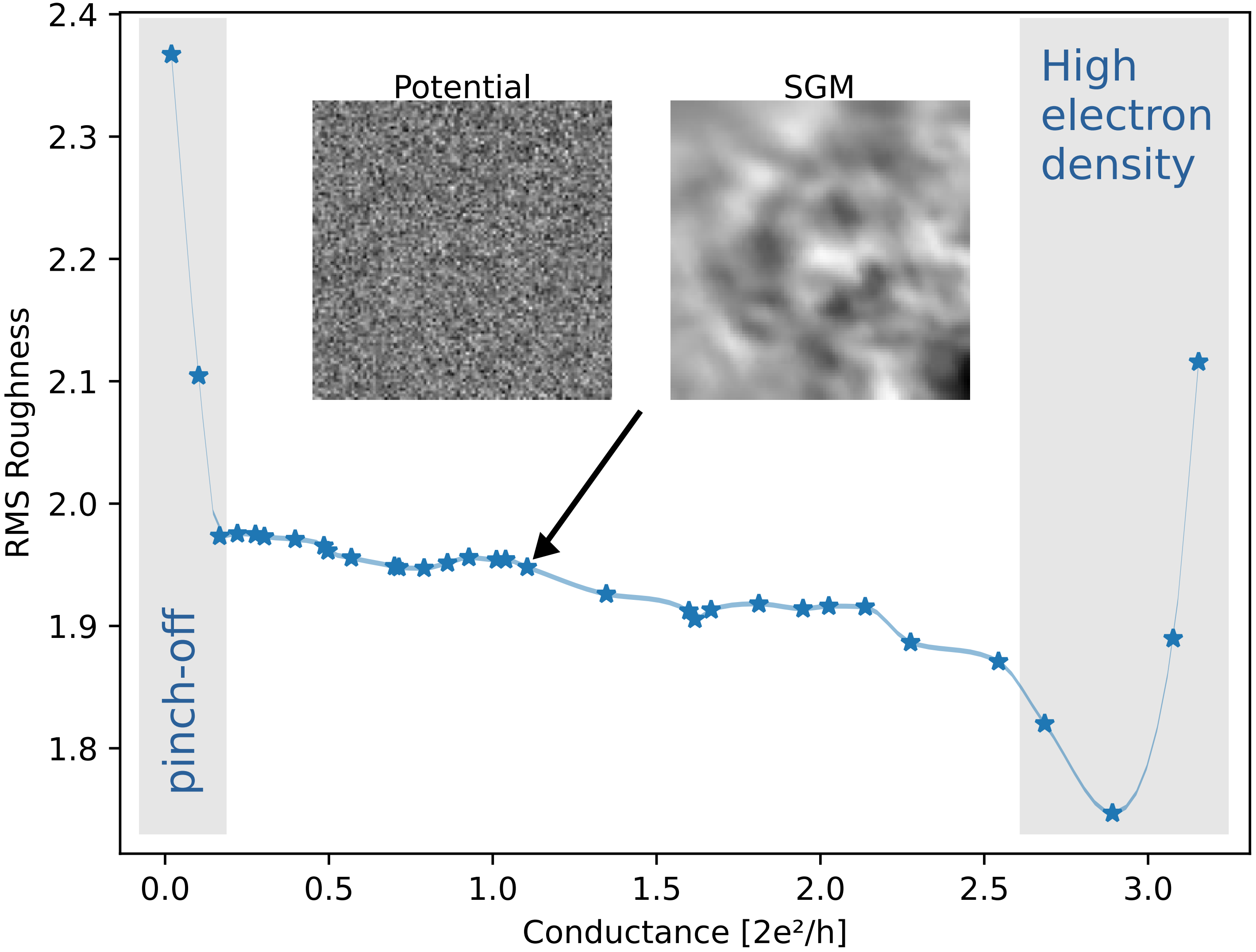


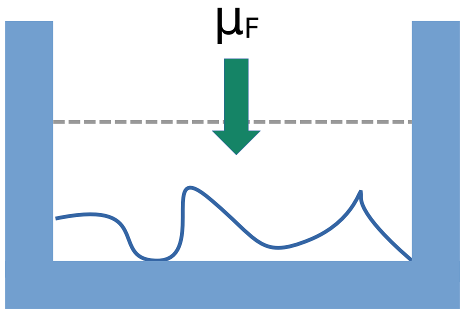
Experimental
(expected)

Generated
(winner)

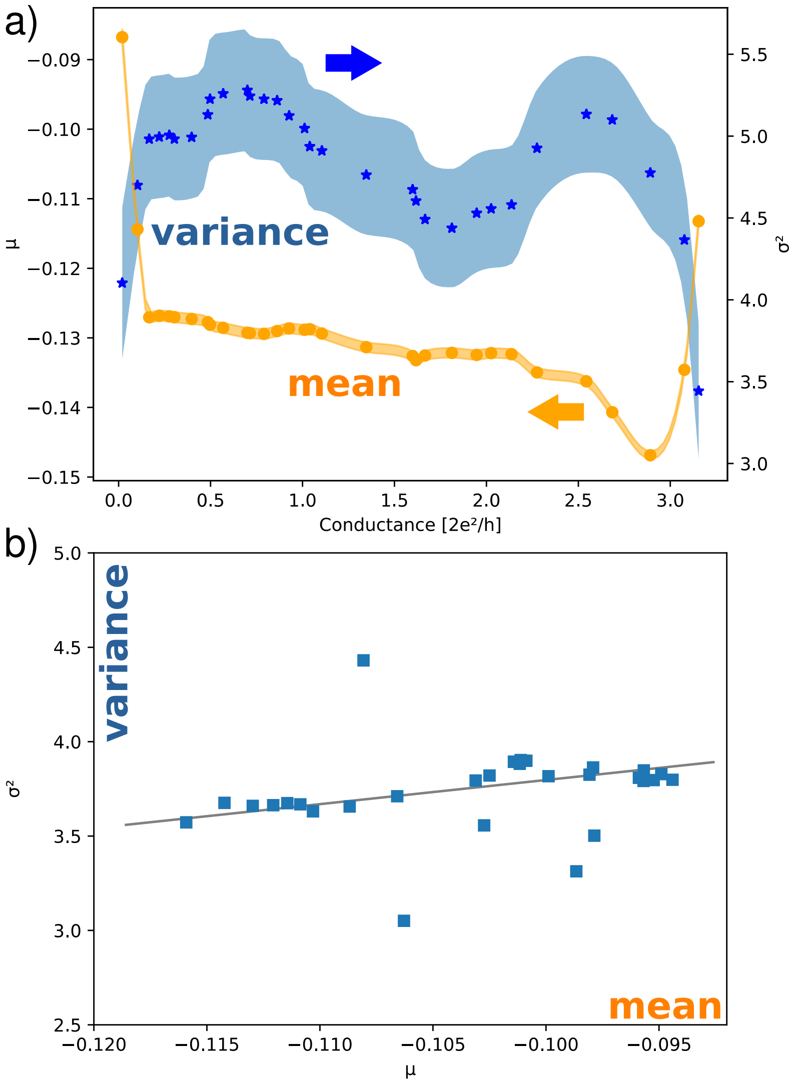
C. R. da Cunha, et al. An investigation of the background potential in quantum constrictions using scanning gate microscopy and a swarming algorithm, *Physica A* **614** (2023) 128550.

Potential Roughness





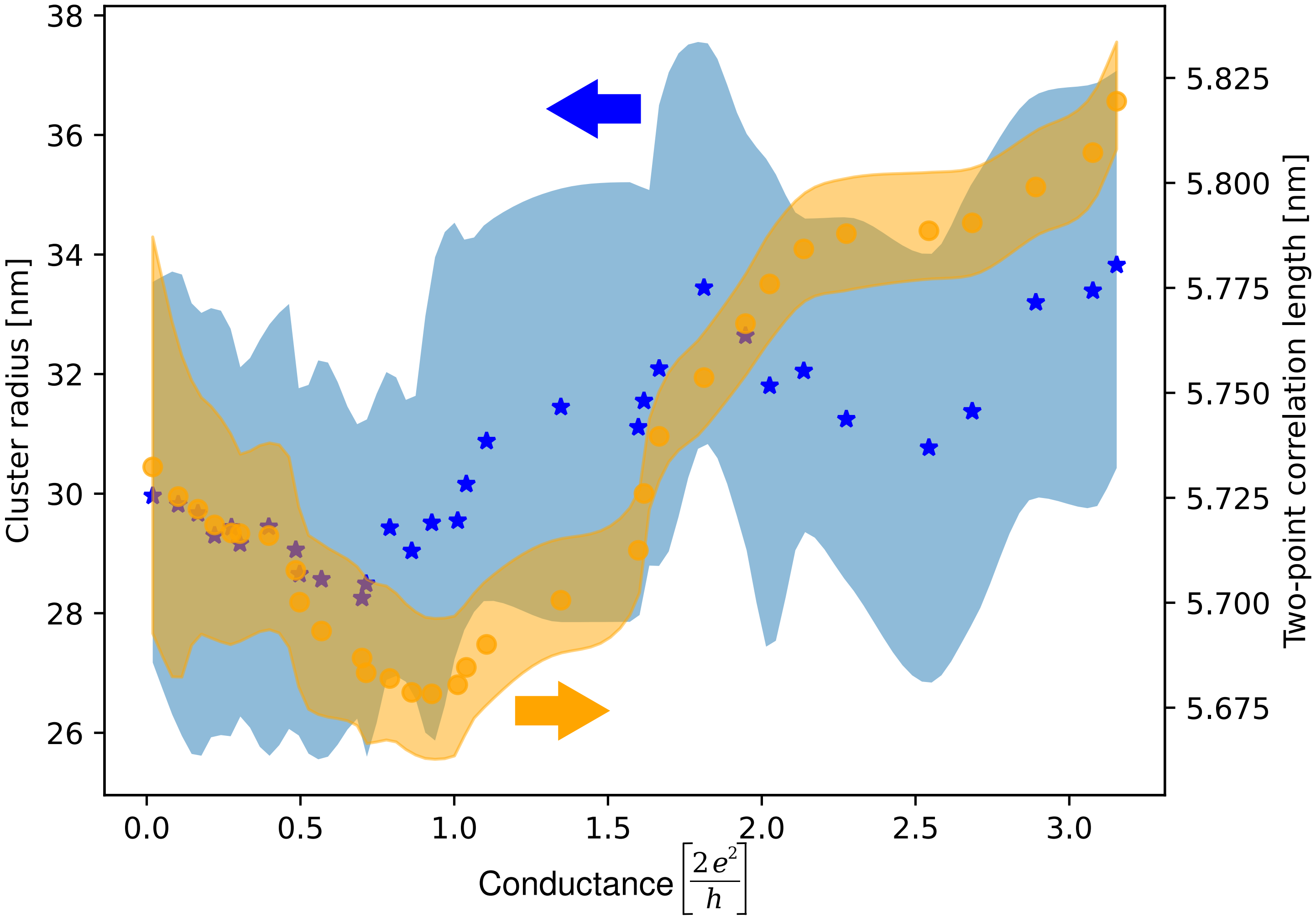
Potential Distribution



No fluctuation scaling.
Equally important points.

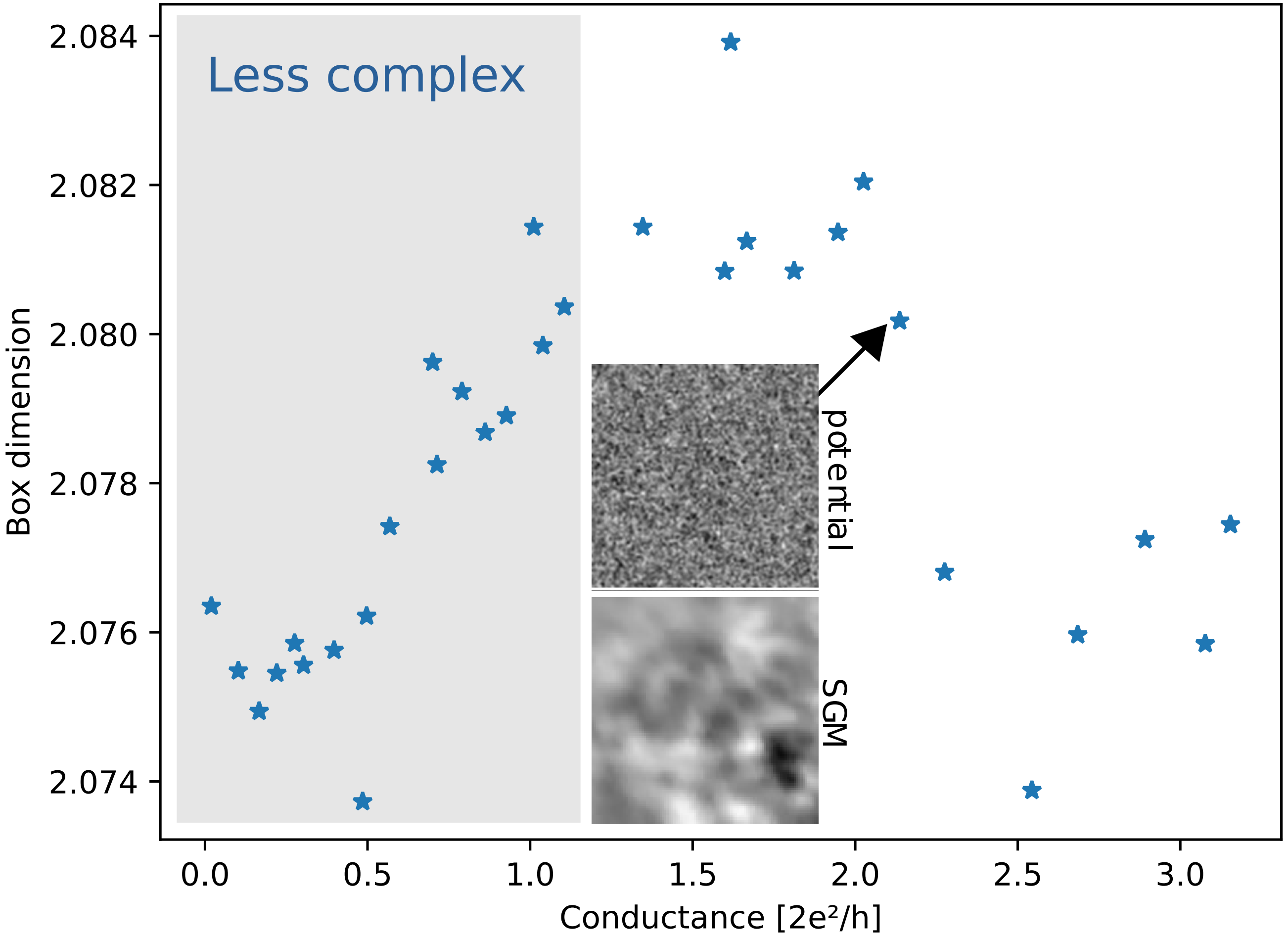
Two-Point Correlation Function

~ Bohr radius



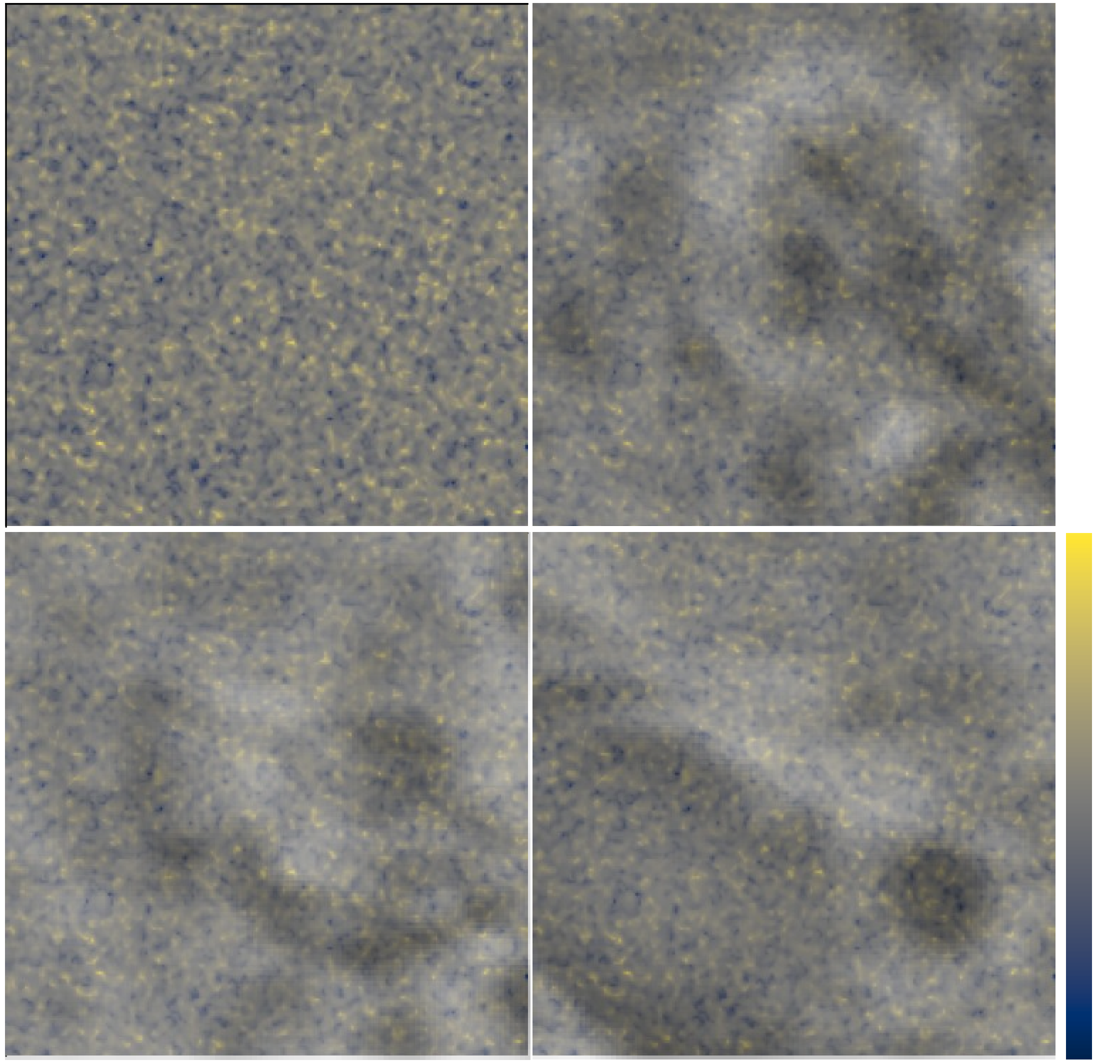
“clumpiness”

Box Dimension



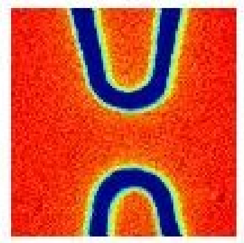
Static Alloy Potential

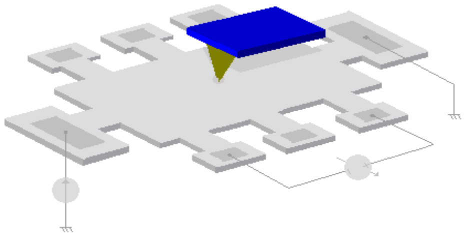
$$U^*_{ij} = \frac{\langle U_{ij} \rangle}{\sigma_{ij}}$$

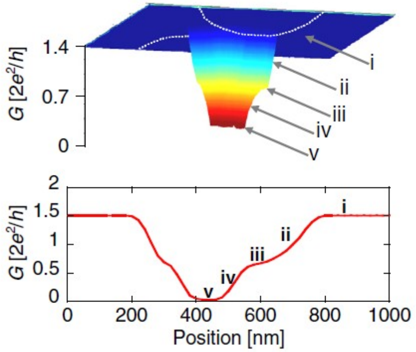


SGM images seem to be influenced by modes supported by the potential.

Conclusions







Quantum Point Contacts

- Case study: Disorder QPC
- SGM: Not simple interpretation
- Standard convolution layers not adequate
- Cellular neural networks are more adequate
- Swarming algorithm gets closer to reality (> 72 %)
- Rough potentials influence images at small base conductance
- All points in the disordered potential are equally important
- SGM images seem to be influenced by modes of the potential

Machine learning

Useful tool for inverse problems (if properly used)
Inverse design of new devices and materials!

Thank You

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Flagstaff, AZ

“Nullius addictus iurare in verba magistri, quo me cumque rapit tempestas, deferor hospes.”
H. Flaccus