



AUTOMATIC DETECTION OF CHARGE TRANSITIONS IN CHARGE STABILITY DIAGRAMS

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1. MOTIVATION

- Semiconductor quantum dot qubits are controlled via gate voltages
 - Plunger gates (P1 P4 in Fig. 1) control the dot potentials
 - Barrier gates (B1 B5 in Fig. 1) control the tunnel barriers
- Tuning large numbers of qubits requires automation
 - Correct number of charges must be trapped in each quantum dot
 - Number of charges is derived from charge transitions in charge stability diagrams (CSDs), in this case measured using a sensor dot
- → Automatic detection of charge transitions enables tuning automation
 - → Goals: good generalization and low complexity for scalability

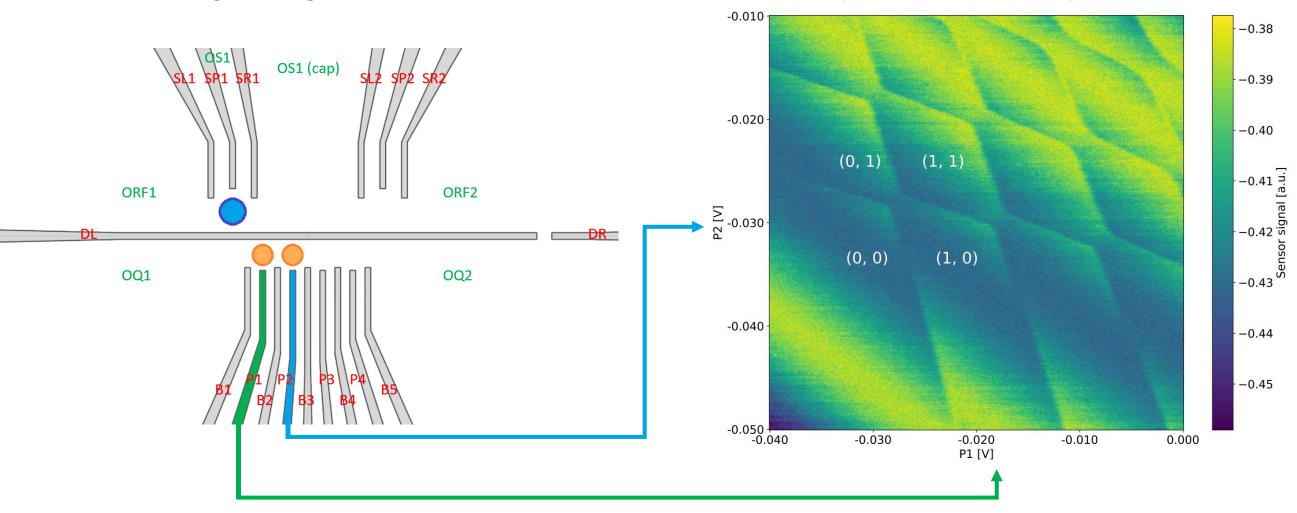
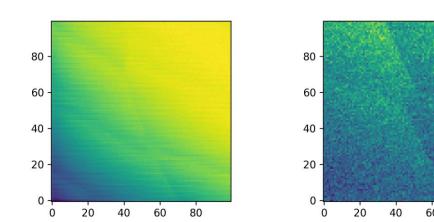
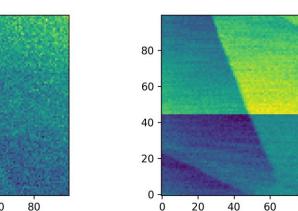
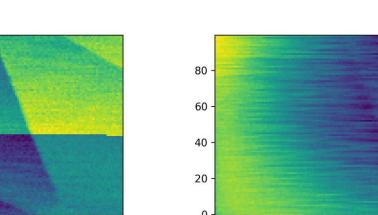


Fig. 1: Example of the gate layout of a semiconductor quantum dot sample (by T. Hangleiter, RWTH, similar to [1]). The blue/orange circles illustrate the regions in which sensor/quantum dots are formed.

Fig. 2: Example of a CSD for a well behaving double quantum dot. The lines indicate a transition of electrons into or out of a dot. In parentheses: exemplary double quantum dot occupation numbers.







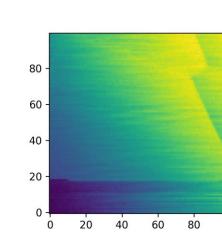


Fig. 3: Examples of measured CSDs with typical distortions. CSDs may feature only weak structures or are affected by strong white noise, random telegraph noise (RTN), and pink noise.

2. METHODS / ALGORITHM DEVELOPMENT

Traditional approaches

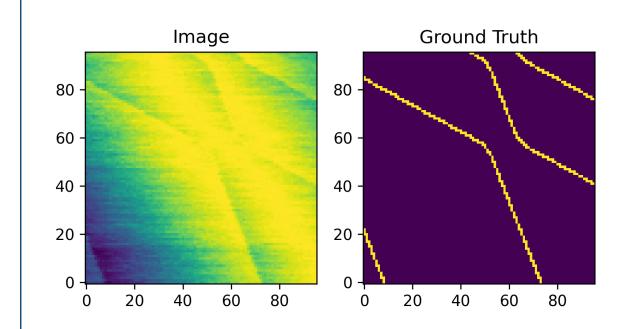
- Gradient based
- Phase congruency based (novel approach)
- Mixed approaches

Machine learning

- Convolution based
- Transformer based
- State space model based
- Diffusion based

CSD Data

- Simulated data from the geometric SimCATS model [2] for parameter optimization and training
 - Pink, white & random telegraph noise, transition blurring, and dot jumps
 - Random variations of charge transitions, sensor, and distortions
 - 10.000 randomly sampled configurations with 100 CSDs each
- Simulated data + experimental data for validation



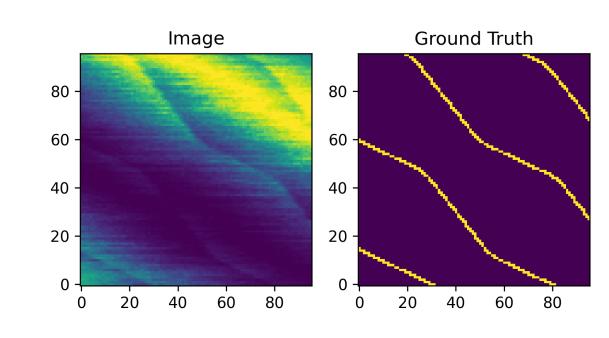


Fig. 4: Examples of simulated CSDs with corresponding ground truth.

3. EXEMPLARY RESULTS

Canny Approach (Traditional, Gradient Based)

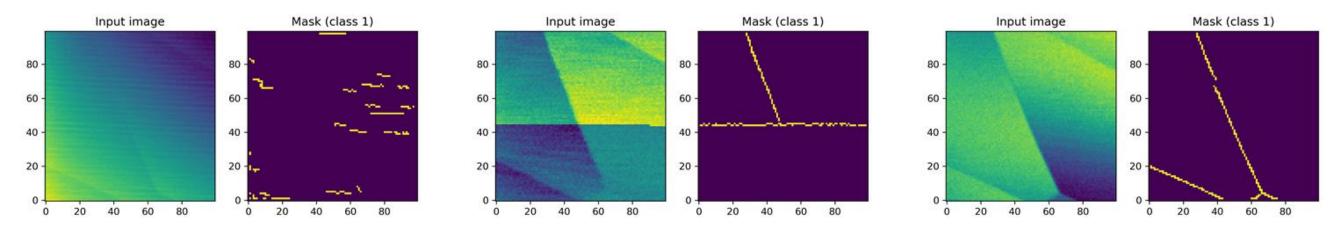


Fig. 5: Charge transition detection on experimental data from the GaAs qubit sample shown in Fig. 1. Left CSD: no valuable information is extracted; center CSD: RTN is detected as charge transition and multiple transitions are missing; right CSD: the majority of charge transitions is detected.

Tiny UNet (Machine Learning, Convolution Based)

Model size reduced by more than 99% (compared to classical UNet)

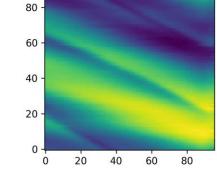
Tab. 1: Statistics for a tiny version of a UNet model developed at ZEA-2. Metrics have been calculated on a simulated validation set.

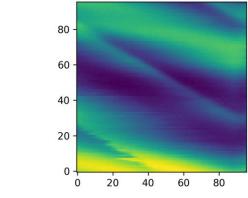
| Model Type | Model Size | Jaccard Similarity | Dice Score | Inference Time (Nvidia L4) |
|---|--|-----------------------|---|--|
| U-Net (Bilinear Upsampling) | 67,425 params | 0.872 | 0.915 | 1.15 ms |
| Input image 80 - 60 - 60 - 40 - 20 - 0 0 2 | Mask (class 1) 80 - 60 - 40 - 20 - 0 0 20 | Input image | ss 1) Input image 80 - 60 - 40 - 20 - 40 60 | Mask (class 1) 80 - 60 - 40 - 20 - 40 60 80 |

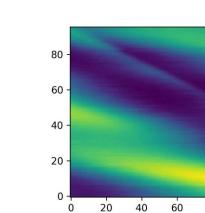
Fig. 6: Charge transition detection on the same experimental data as shown in Fig. 5. All charge transitions are detected. The network ignores the RTN in the center CSD without leading to a wrong detection.

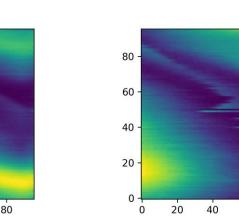
4. OUTLOOK

- Final evaluation & selection of machine learning and traditional approaches
- Testing with further experimental data
 - SiGe sample
 - Live in the experiment









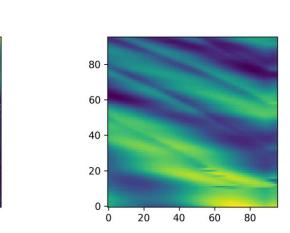


Fig. 7: Examples of single dot plunger vs. barrier CSDs from a SiGe sample.

- Further complexity reduction & improvement of robustness
 - Automated machine learning (AutoML)
 - Hyperparameter optimization (HPO)
 - Neural Architecture Search (NAS)
 - Introduction of verification strategies & explainable AI (XAI)
- → Long term goal: hardware implementation



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