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Orientation, Pattern Center Refinement and Deformation State Extraction through Global Optimization Algorithms

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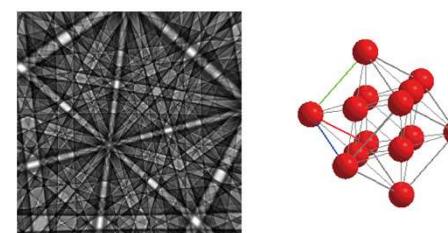
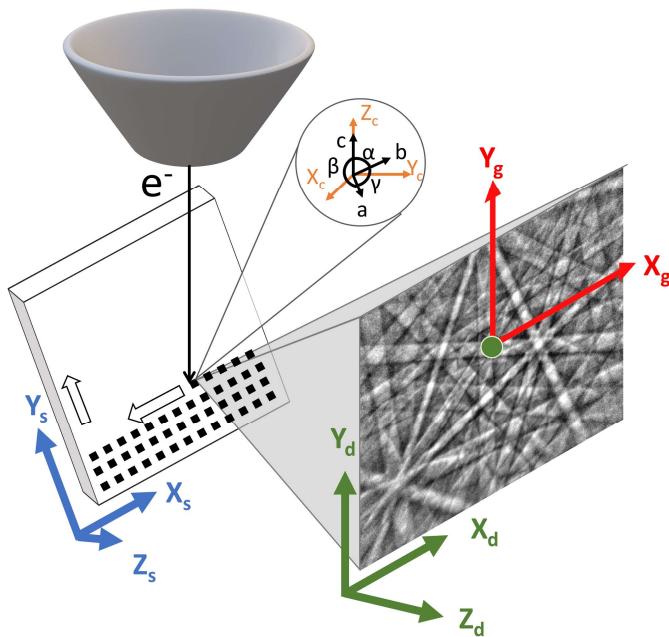
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Electron Backscatter Diffraction

Electron backscatter diffraction is a fully automated SEM-based characterization technique to extract structural information from materials to study their microstructure, texture, defect density, residual strain, etc.



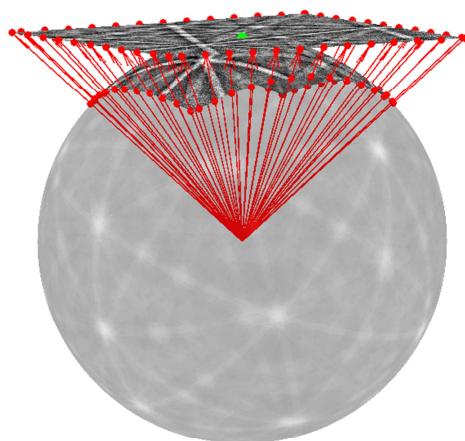
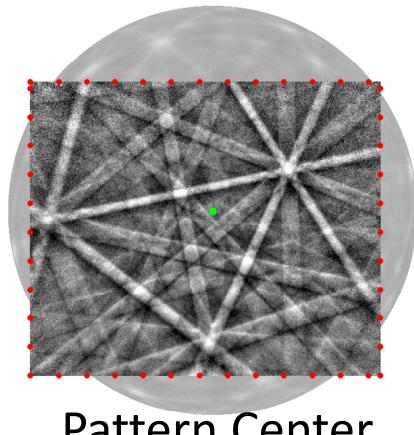
0.5% in pattern center
->
Strain uncertainty $\sim 3 \cdot 10^{-3}$

The Pattern Matching Problem

Forward model (f) describing the accurate diffraction physics:

$$I_{\text{simulated}} = f(\text{keV, phase, geometry, orientation, pattern center, elastic deformation})$$

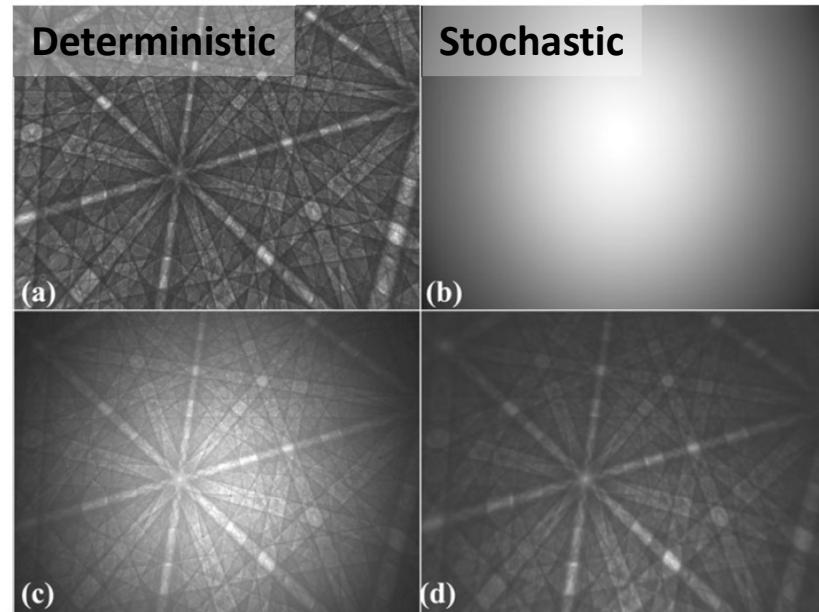
Known Partially known Unknown



How do we improve the similarity between
 $I_{\text{simulated}}$ and $I_{\text{experimental}}$?

- Realistic forward model (f)
- Improve the accuracy of orientation and PC
- Determine the elastic deformation tensor

Dynamical Simulation of EBSD Pattern: Forward Model



Ground truth: Ni @ 30keV

Deterministic part: dynamical scattering model uses scattering matrix to predict probability of BSE distribution.

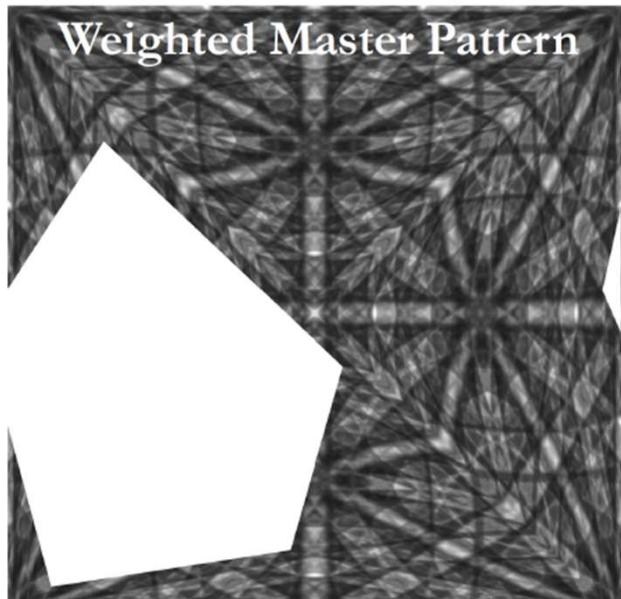
Stochastic part: Monte Carlo electron trajectory simulation to predict spatial and energy distributions for BSEs.

Geometric part: geometrical parameters-detector tilt, sample tile, crystal orientation, pattern center, deformation tensor.

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Approximate Model for Deformation Tensor Inclusion

$$(X, Y)_L = \ell(F^{-1}(L_q[\hat{p}]))$$



Weighted Master Pattern
Approximate Deformation Model

Rotated and Undeformed Pattern Coordinates:

$$(X, Y)_L = \mathcal{L}(L_q[\hat{p}])$$

\hat{p} : detector pixel coordinates

L_q : quaternion rotation operator

q: (passive) rotation required to rotation

\mathcal{L} : square Lambert transformation.

Rotated and Deformed Pattern Coordinates:

$$(X, Y)_L' = \mathcal{L}(F^{-1}(L_q[\hat{p}]))$$

F^{-1} : interpolation on the undeformed master

Formulation of the Optimization Problem

Definition of an optimization problem:

$$\max_{x \in S} \text{sim}(f(x), I_{\text{experimental}})$$

seek for a minimizer x^* that gives best match with the experimental pattern:

$$\text{sim}(f(x^*), I_{\text{experimental}}) \geq \text{sim}(f(x), I_{\text{experimental}})$$

Bounded optimization problem:

Initial estimate: orientation=($\varphi_1, \Phi, \varphi_2$), PC=(PCx, PCy, DD)

Optimized values: orientation*=($\varphi_1, \Phi, \varphi_2$) · s, PC * =(PCx, PCy, DD) + pc

What about deformation?

sim: similarity metric; x: n-dimensional parameter vector; S: subset of \mathbb{R}^n

Formulation of the Optimization Problem

Elastic deformation tensor contains the rotation and stretch:

Optimized values : PC* = (PCx, PCy, DD) + pc

Elastic deformation tensor (8 degrees of freedom):

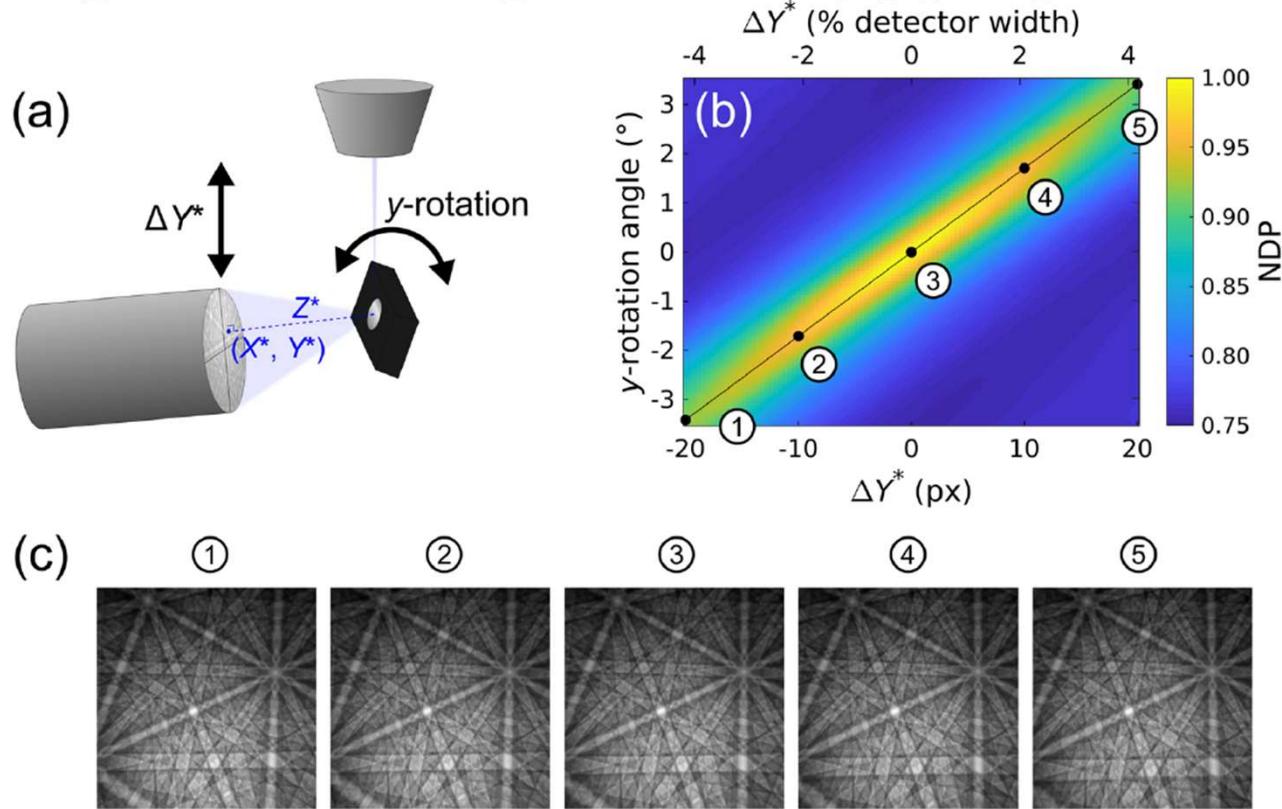
$$F = I + \begin{pmatrix} \Delta\beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \Delta\beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & 0 \end{pmatrix} + \beta_{33} I$$

EBSD insensitive to spherical strain!!!

For isotropic elastic material ($\sigma_{33} = 0$; orientation=[0,0,0]):

$$\boxed{\beta_{33} = \frac{-\lambda(\Delta\beta_{11} + \Delta\beta_{22})}{3\lambda + 2G}} \quad \lambda = \frac{Ev}{(1 + v)(1 - 2v)} \quad G = \frac{E}{2(1 + v)}$$

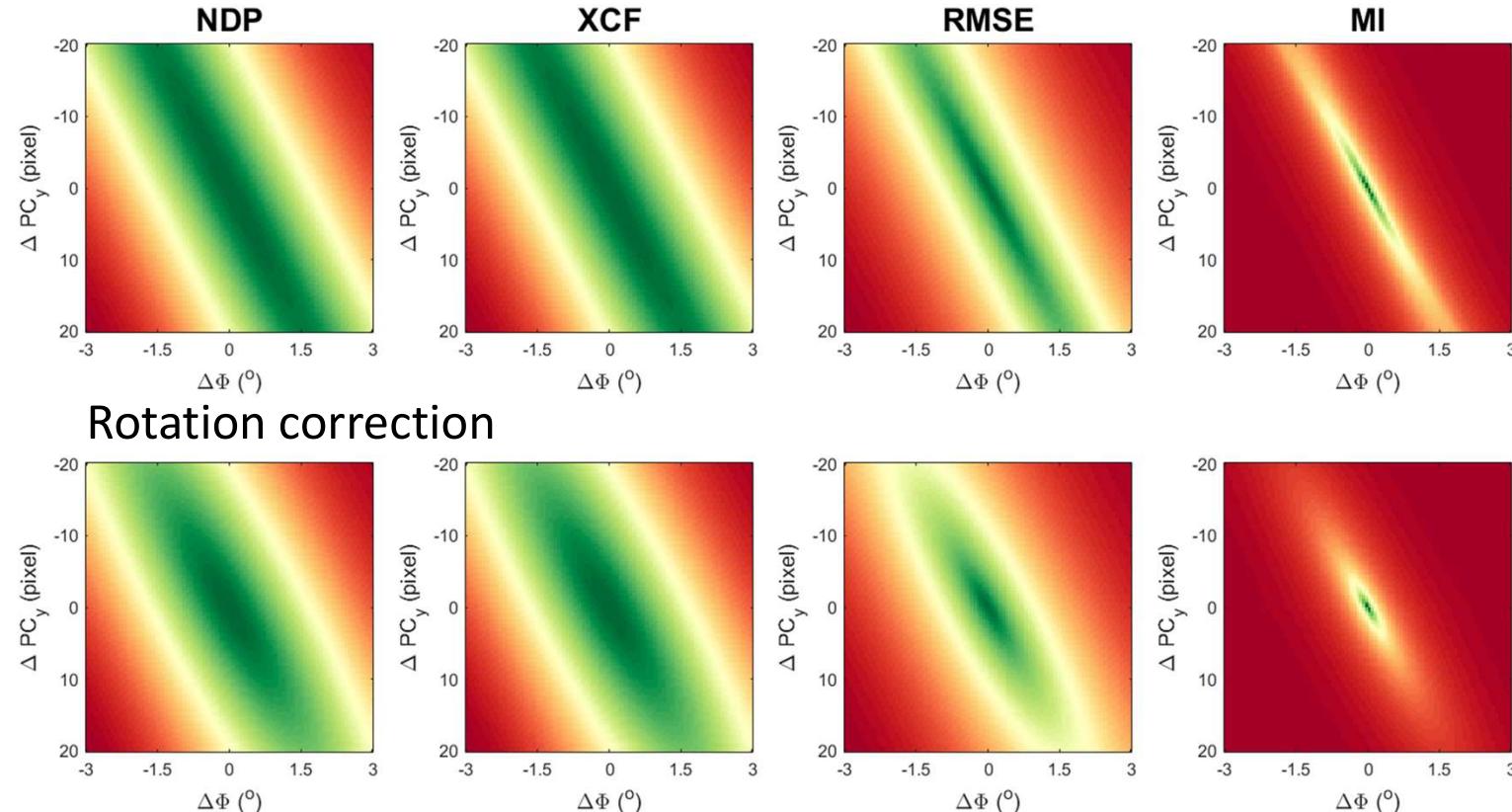
Challenge in Convergence: Sloppy Optimization



Pattern center shift can be compensated by small rotation.
Nelder-Mead simplex can't converge efficiently

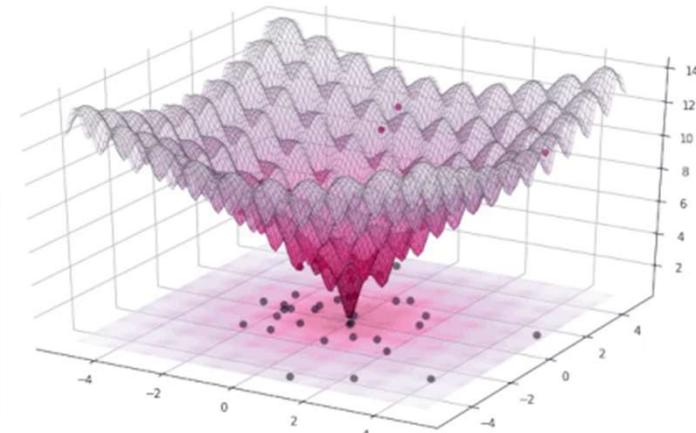
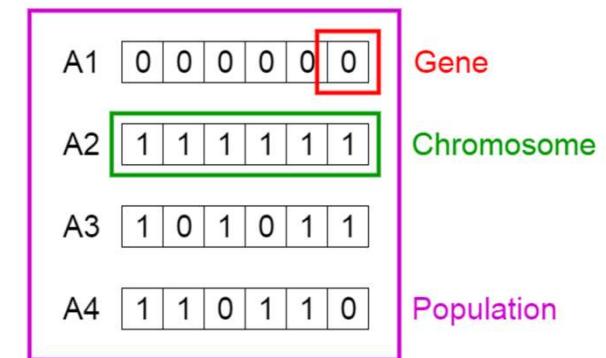
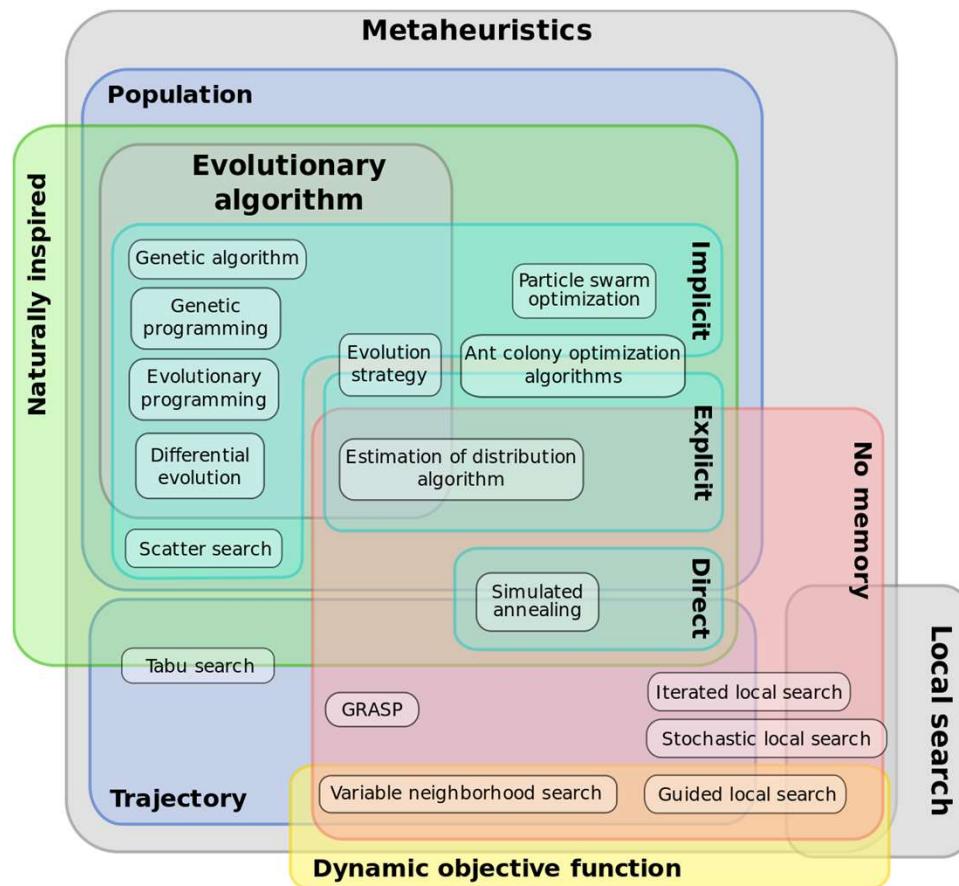
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Sloppy Feature Scaling: Rotation Correction



The sloppiness is universal to all the similarity metrics.

Population Based Global Optimization



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Differential Evolution Algorithm

Initialization $x_{i,g} = x_{j,i,g} \quad j \in \{1, \dots, D\}, i \in \{1, \dots, N_p\}, g \in \{1, \dots, g_{max}\}$

Mutation $v_{i,g+1} = x_{r_1,g} + F(x_{r_2,g} - x_{r_3,g})$ DE/rand/1

$v_{i,g+1} = x_{r_1,g} + F(x_{r_2,g} + x_{r_3,g} - x_{r_4,g} - x_{r_5,g})$ DE/rand/2

$v_{i,g+1} = x_{i,g} + F(x_{best,g} - x_{i,g} + x_{1,g} - x_{r_2,g})$ DE/rand-to-best/1

$v_{i,g+1} = x_{best,g} + F(x_{r_1,g} - x_{r_2,g})$ DE/best/1

$v_{i,g+1} = x_{best,g} + F(x_{r_1,g} + x_{r_2,g} - x_{r_3,g} - x_{r_4,g})$ DE/ best /2

Crossover $u_{i,g+1} = u_{j,i,g+1} \begin{cases} v_{j,i,g+1} & \text{if } rand_j \leq C_r \text{ or } j = j_{rand} \\ x_{j,i,g} & \text{otherwise} \end{cases}$

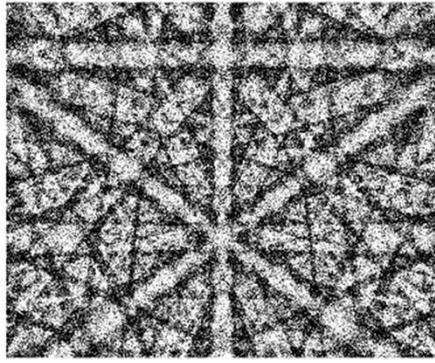
Selection $x_{i,g+1} = \begin{cases} u_{i,g+1} & \text{if } f(u_{i,g+1}) \leq f(x_{i,g}) \\ x_{i,g} & \text{otherwise} \end{cases}$

Hyperparameter Tuning

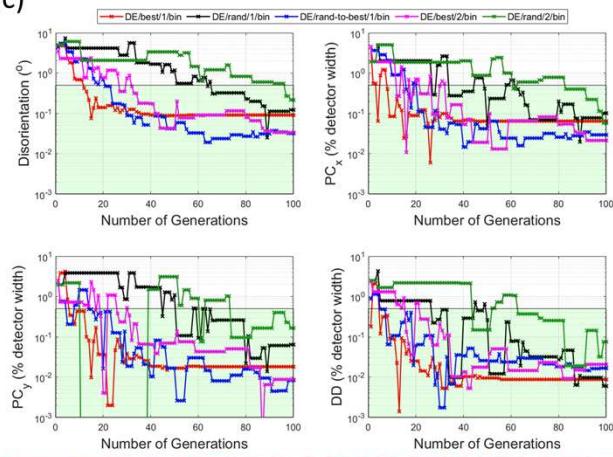
- Crossover probability (C_r): 0.7-0.9 (default:0.9)
- Mutation factor (F): 0.2-0.5 (default:0.5)
- Number of generations (g_{max}): 50-100 (default:100)
- Initial Population size (N_p): 10D

Mutation Schemes

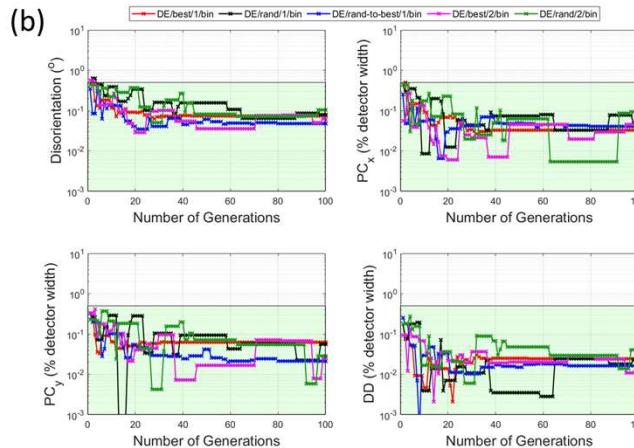
(a)



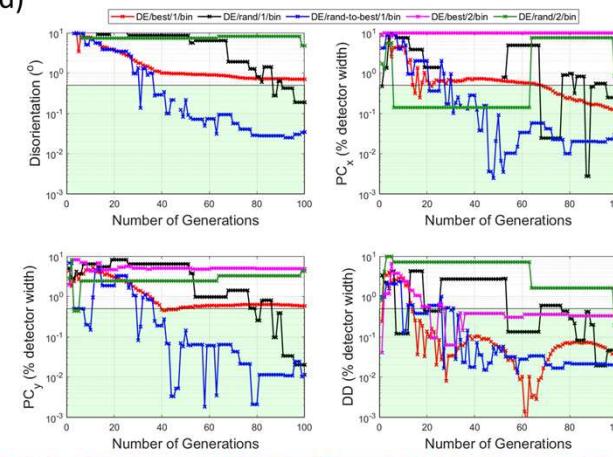
(c)



(b)



(d)



Search spaces:

(a) 11.72 dB noise

(b) $\pm 0.5^\circ$, $\pm 0.5\%$

(c) $\pm 10^\circ$, $\pm 5\%$

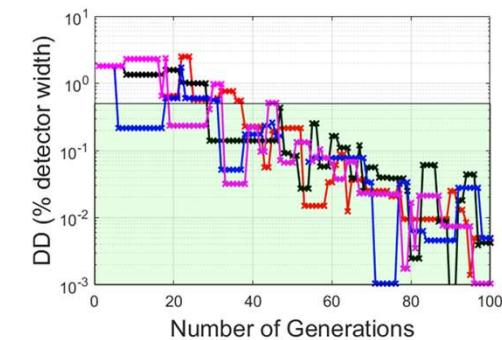
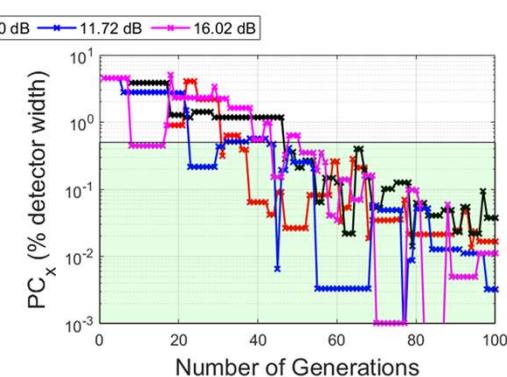
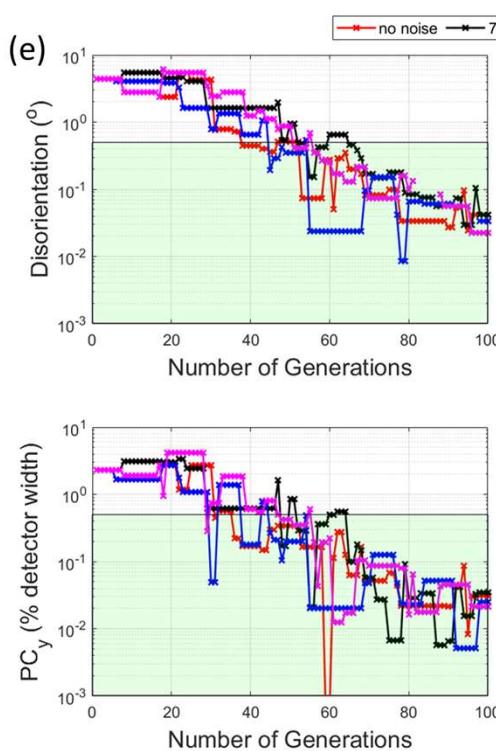
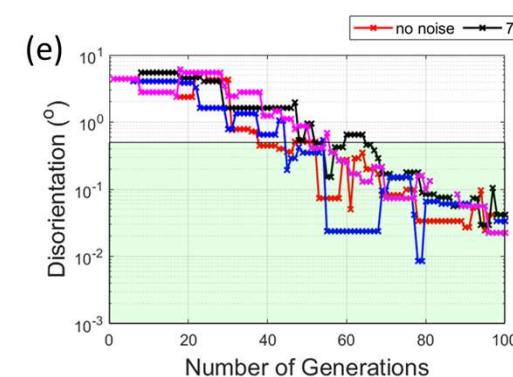
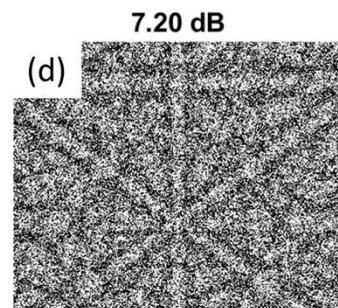
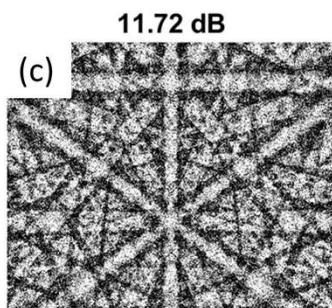
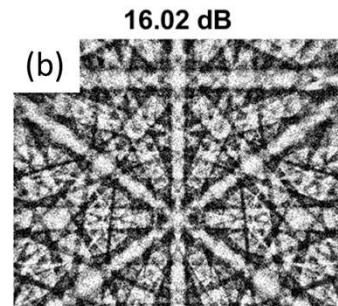
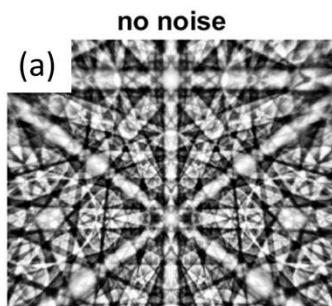
(c) $\pm 20^\circ$, $\pm 10\%$

DE/rand-to-best/1

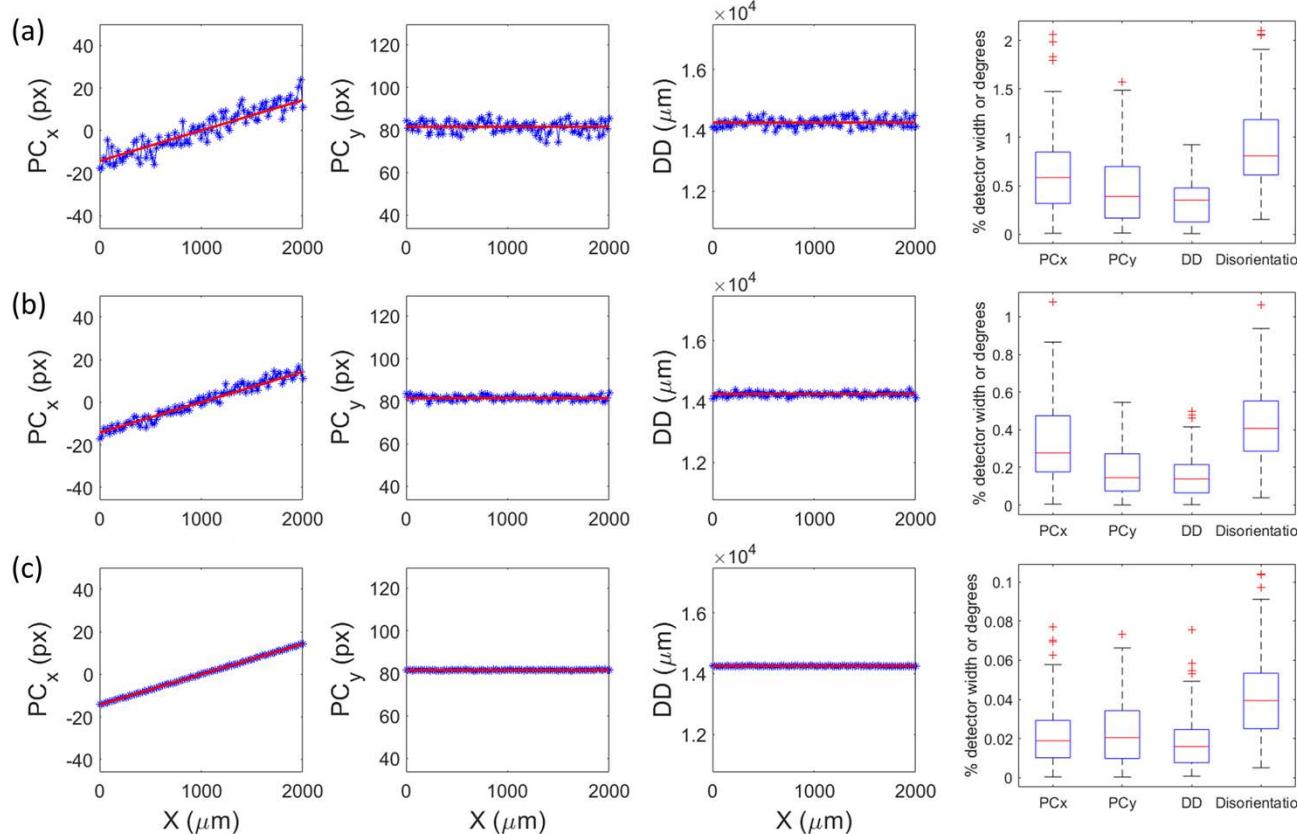
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Noise sensitivity

$g_{\max}=100$, $N_p=60$, $Cr=0.9$ and $F = 0.5$ (DE/rand/1)



Hybrid Optimization: DE+NMS



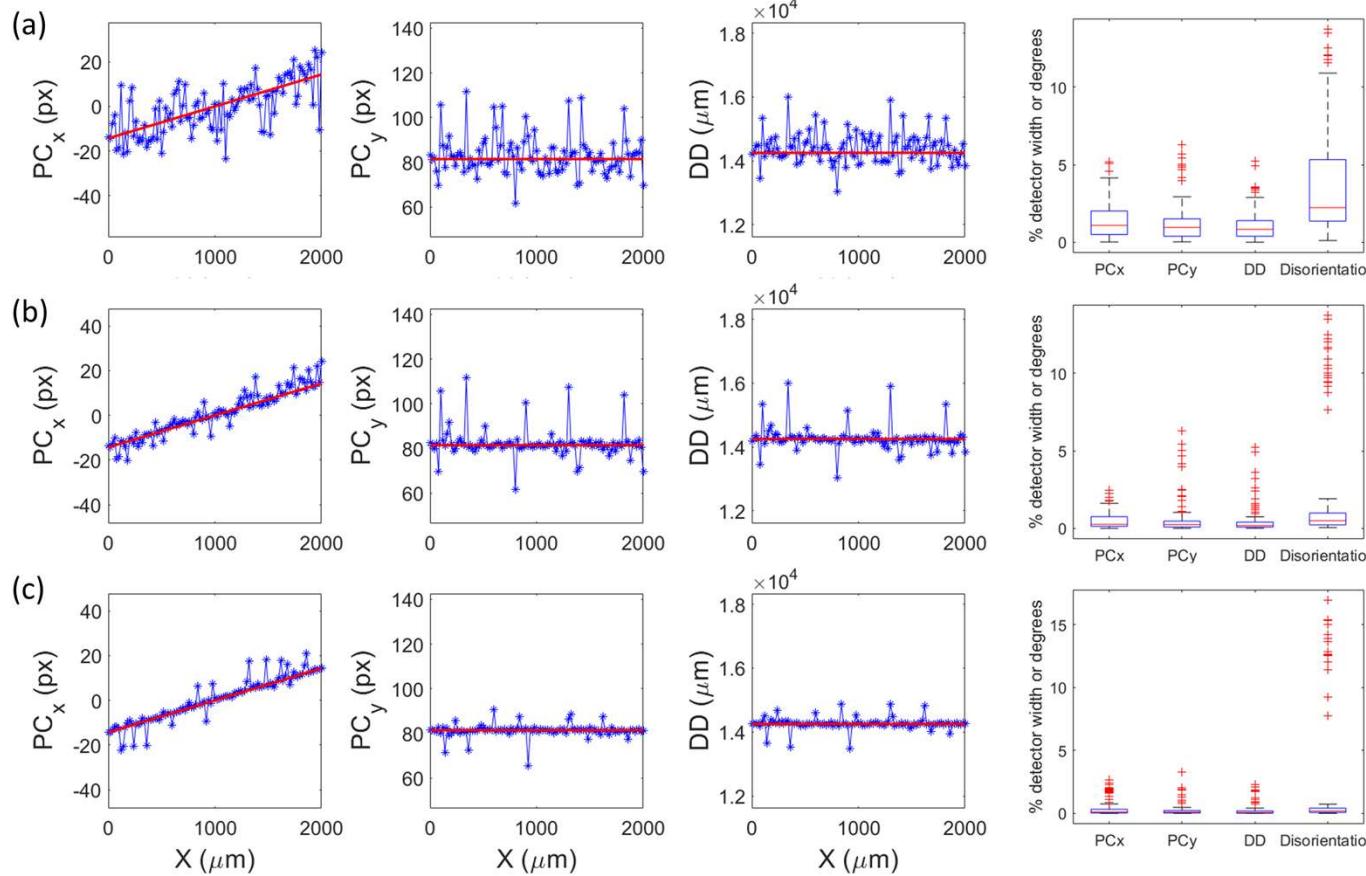
$g_{\max} = 50$

$g_{\max} = 50 + \text{NMS}$

$g_{\max} = 100 + \text{NMS}$

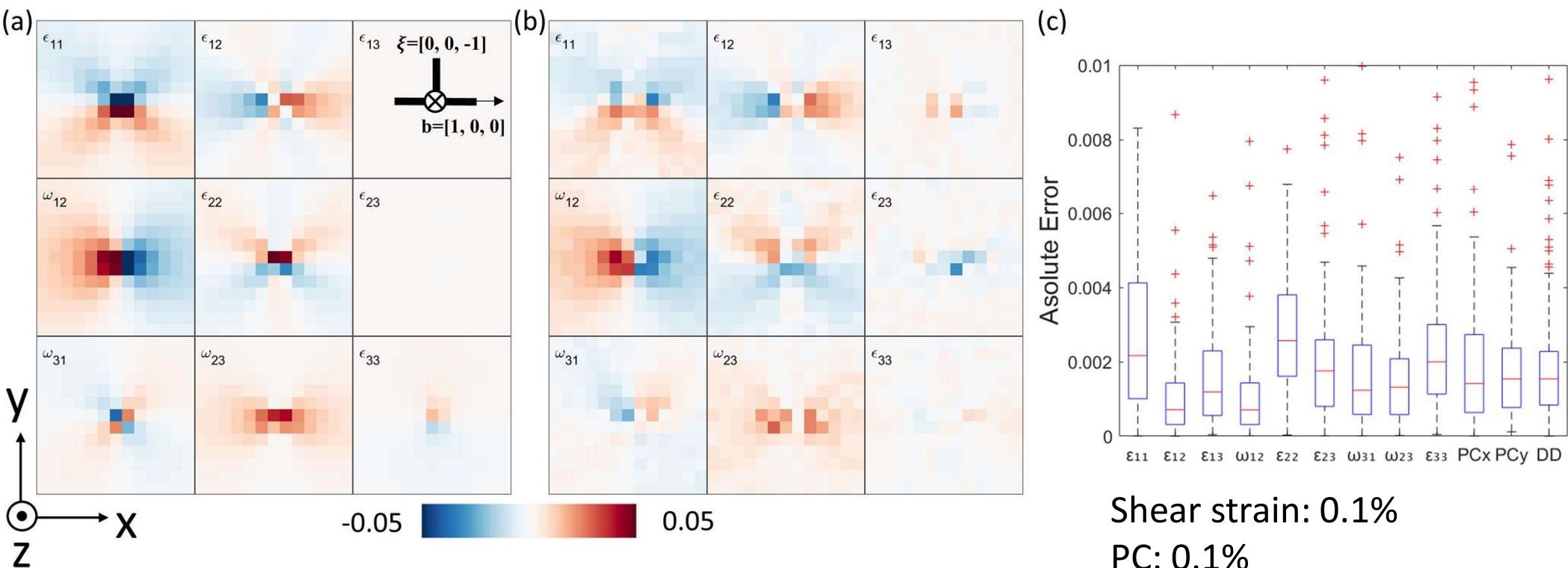
0.02% d.w. for pattern center and 0.04 degrees for the orientation

Hybrid Optimization: PSO+NMS



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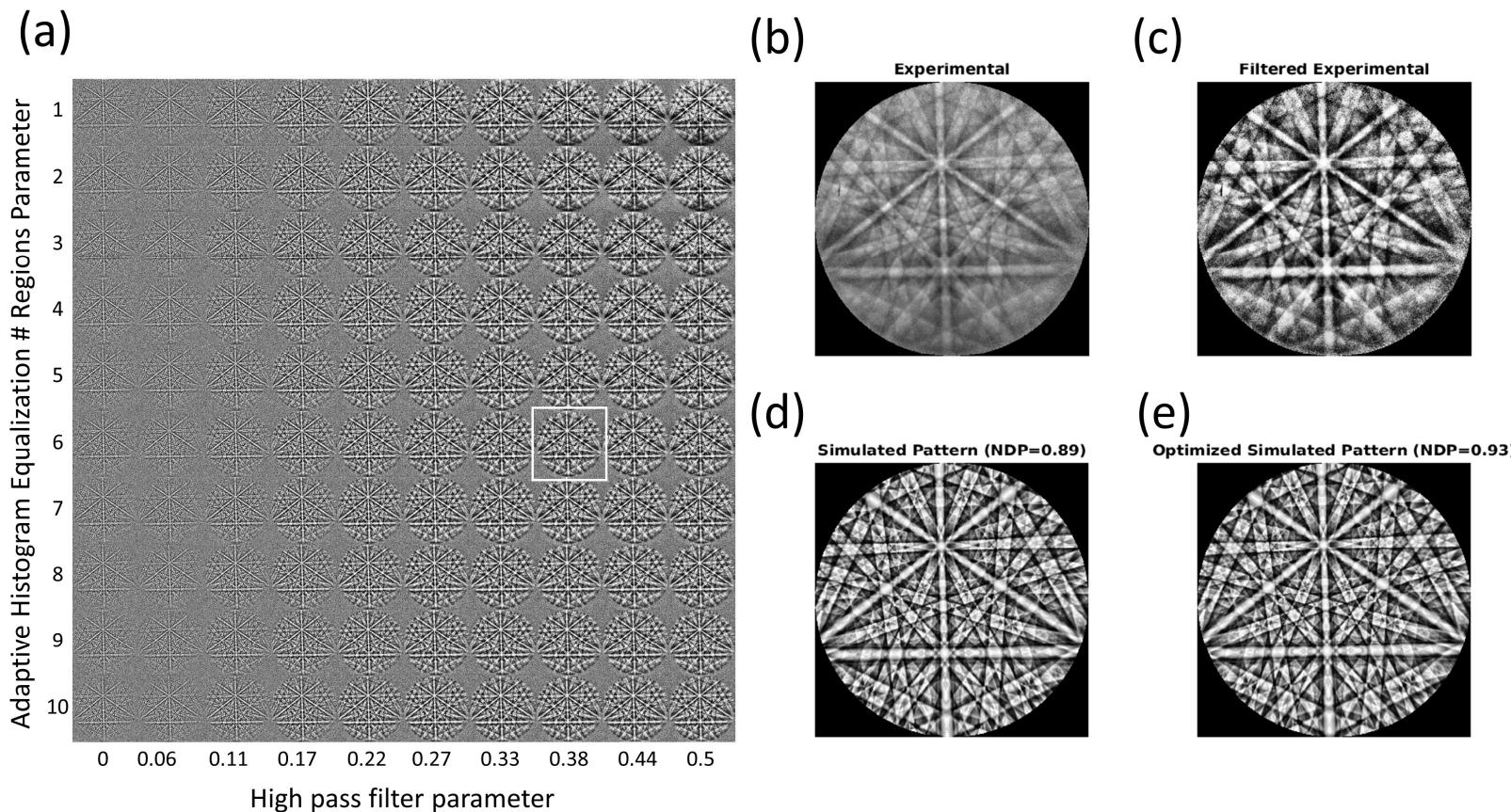
Deformation Tensor Inference: Simulated Patterns



Absolute Strain Mapping with Any Reference Pattern

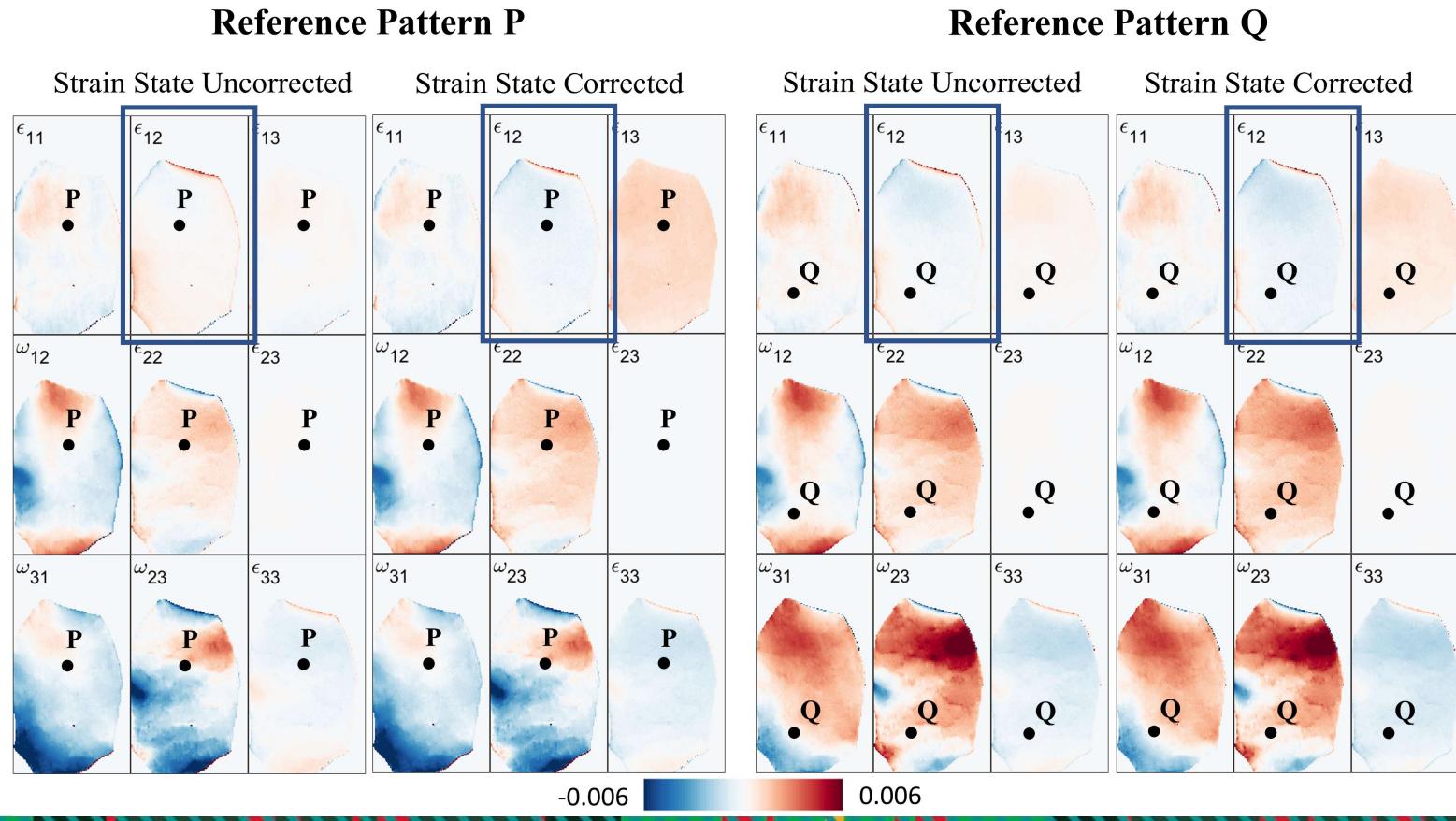
1. Pattern pre-processing: adaptive histogram equalization, high-pass/low-pass filter
2. Determine the reference pattern to be used and optimize its PC and orientation
3. Use optimized PC and determine the strain tensor of reference pattern
4. Use cross-correlation based HR-EBSD to determine the strain map relative to reference
5. Strain state correction based on strain state of the reference pattern

Experimental Pattern Pre-Processing



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Experimental Validation: Low Cycle Fatigued TRIP Steel



Summary

- The differential evolution algorithm outperforms particle swarm algorithm due to the nature of mutation.
- The search space for differential evolution is feasible up to ± 20 disorientation and $\pm 10\%$ detector width.
- Simulated undeformed patterns demonstrate an accuracy of $\sim 0.04^\circ$ for orientation and $\sim 0.02\%$ detector width for pattern center.
- Noisy simulated deformed patterns reveal an accuracy of shear strain and rotation components ~ 0.001 and ~ 0.002 for the normal strain.

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Other people in the group: Marcus Ochsendorf, Christian Kurniawan, Maxwell Lee, Ke-wei Jin, Michael Kitcher, Clement Lafond

Github Link: <https://github.com/EMsoft-org/EMsoft>