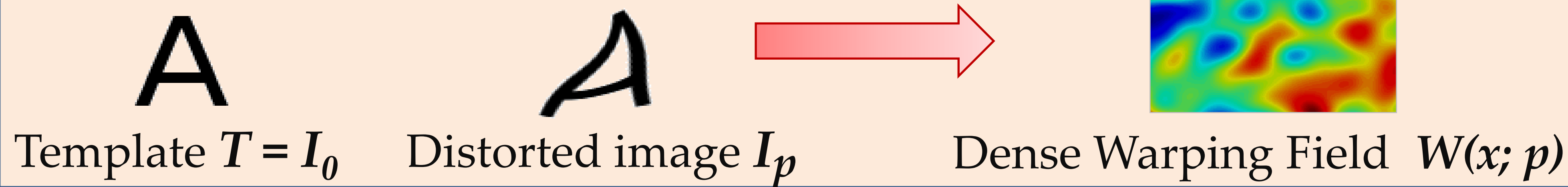


A Globally Optimal Data-driven Approach for Image Distortion Estimation

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Problem Statement



Distortion Model

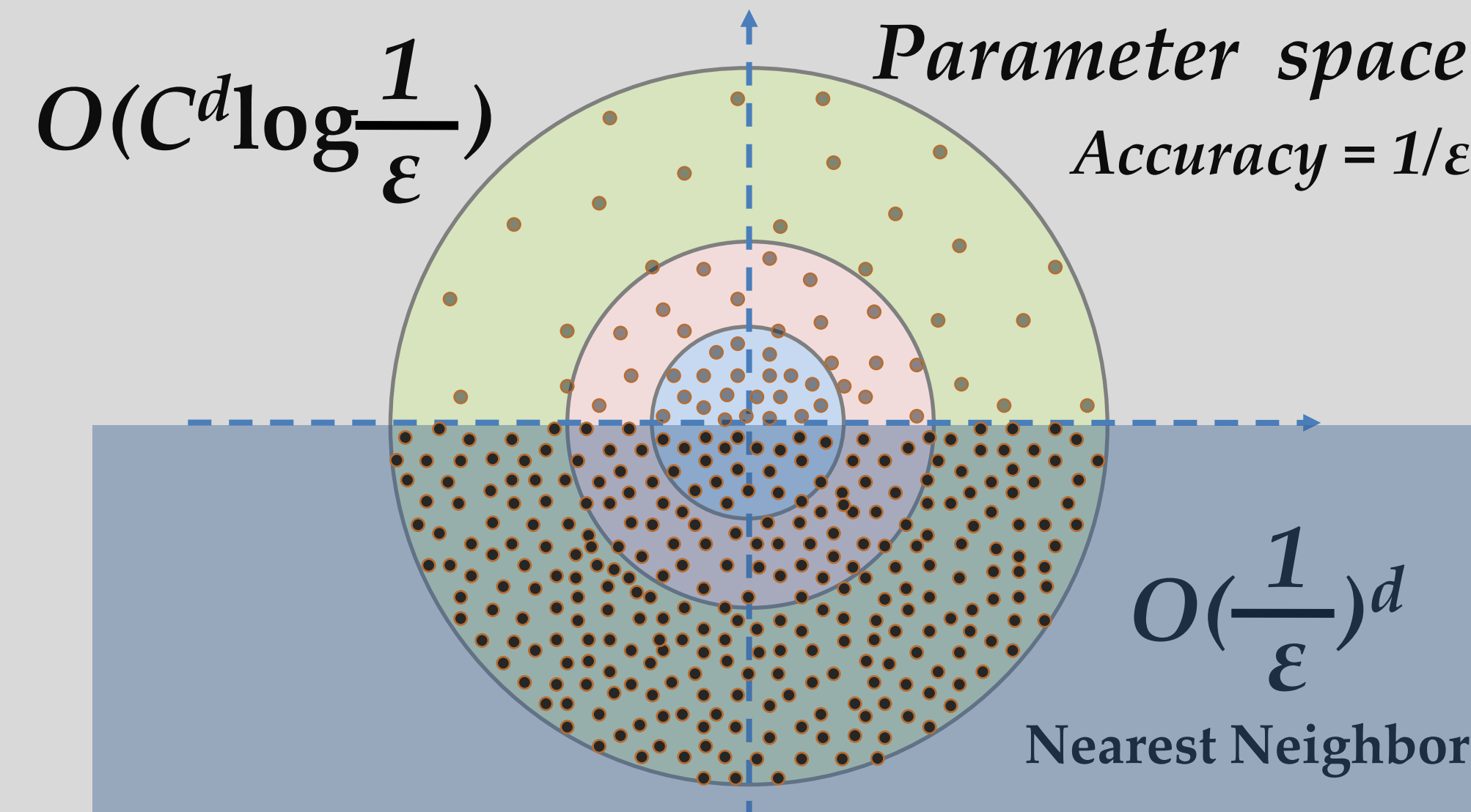
$$W(x; p) = x + B(x)p$$

Bases $B(x)$ → •Linear & Rigid
•Spatial nonlinearity
•Measurement-based
Parameters p → Fewer dimensions

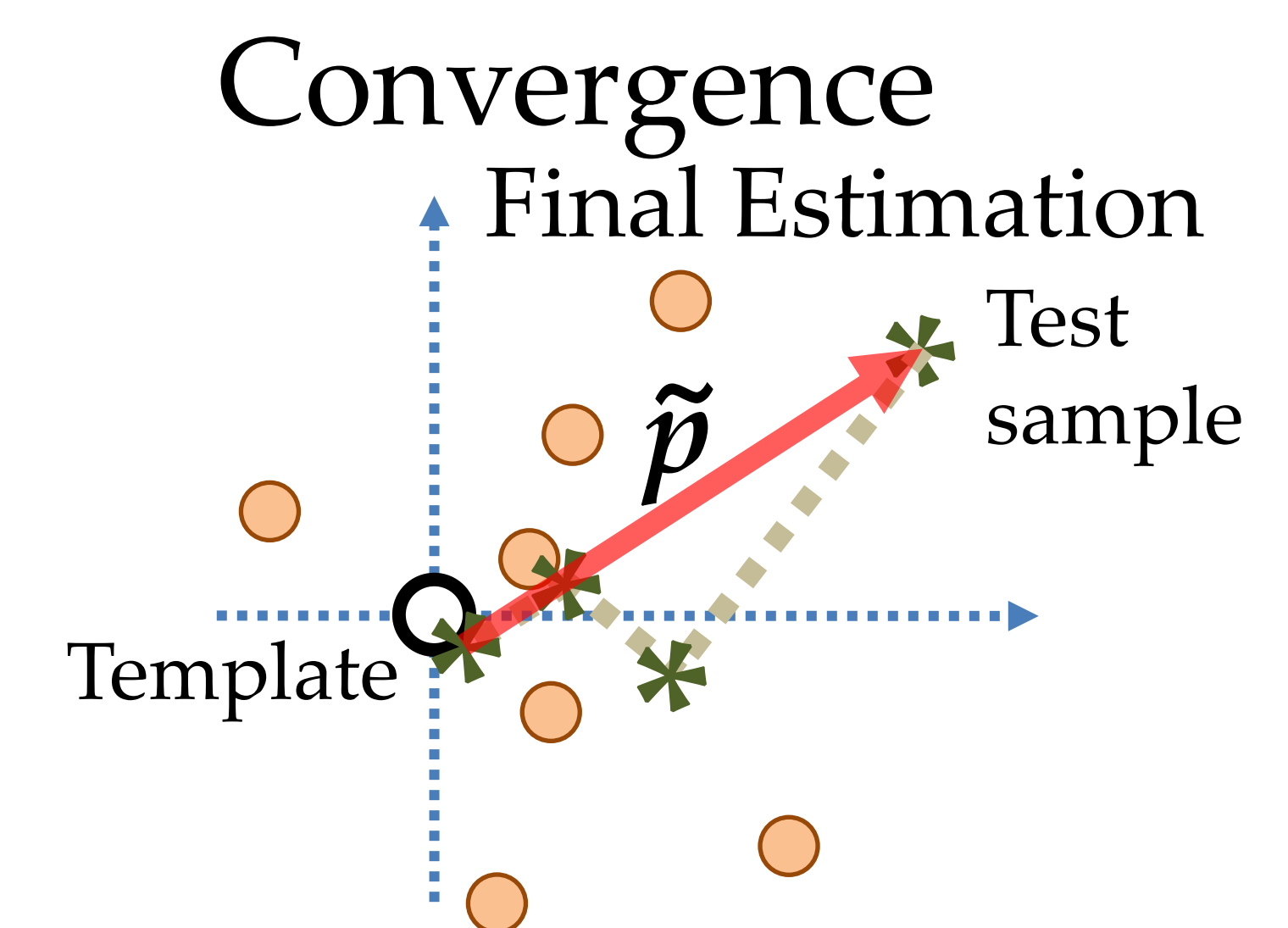
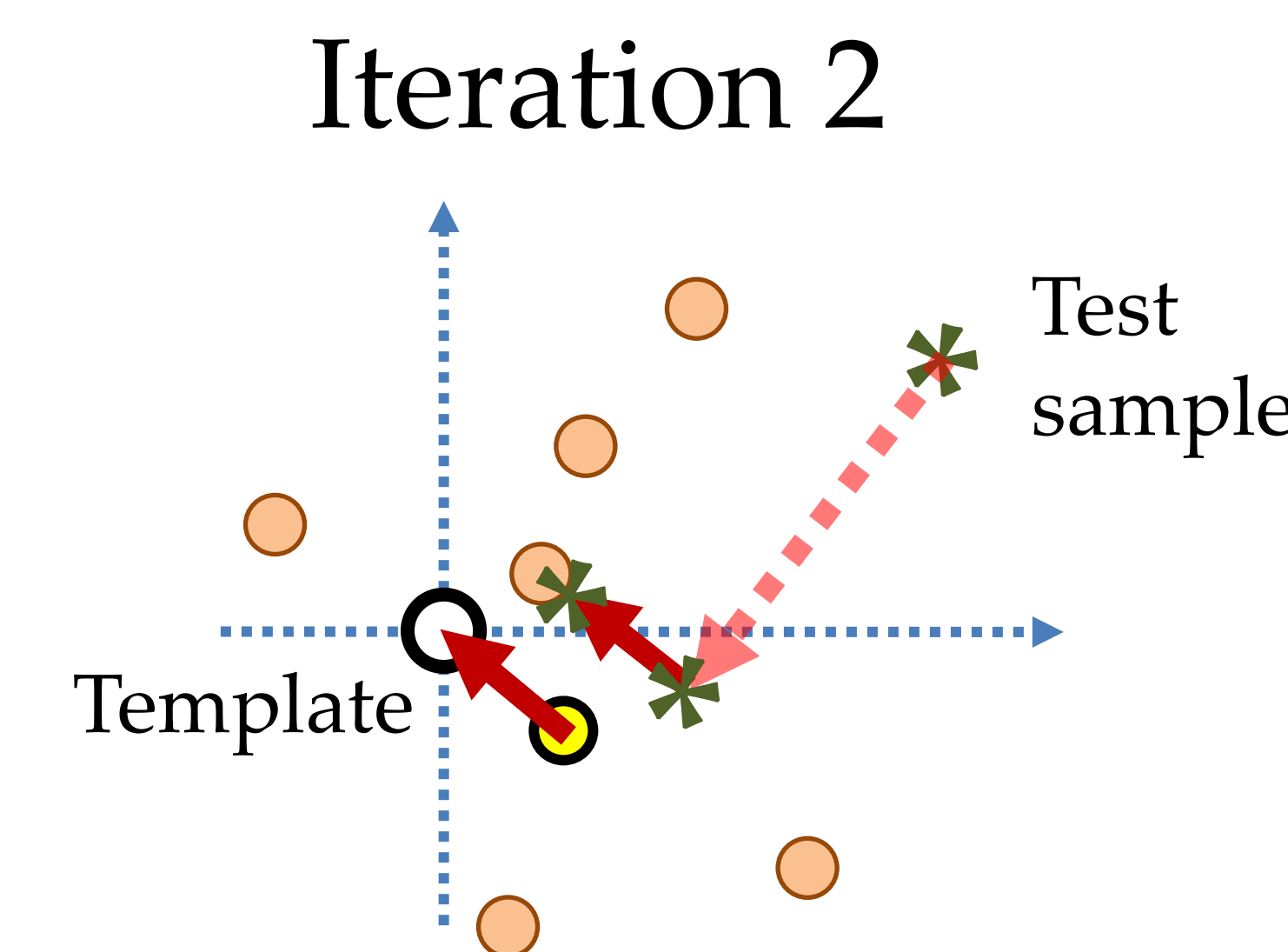
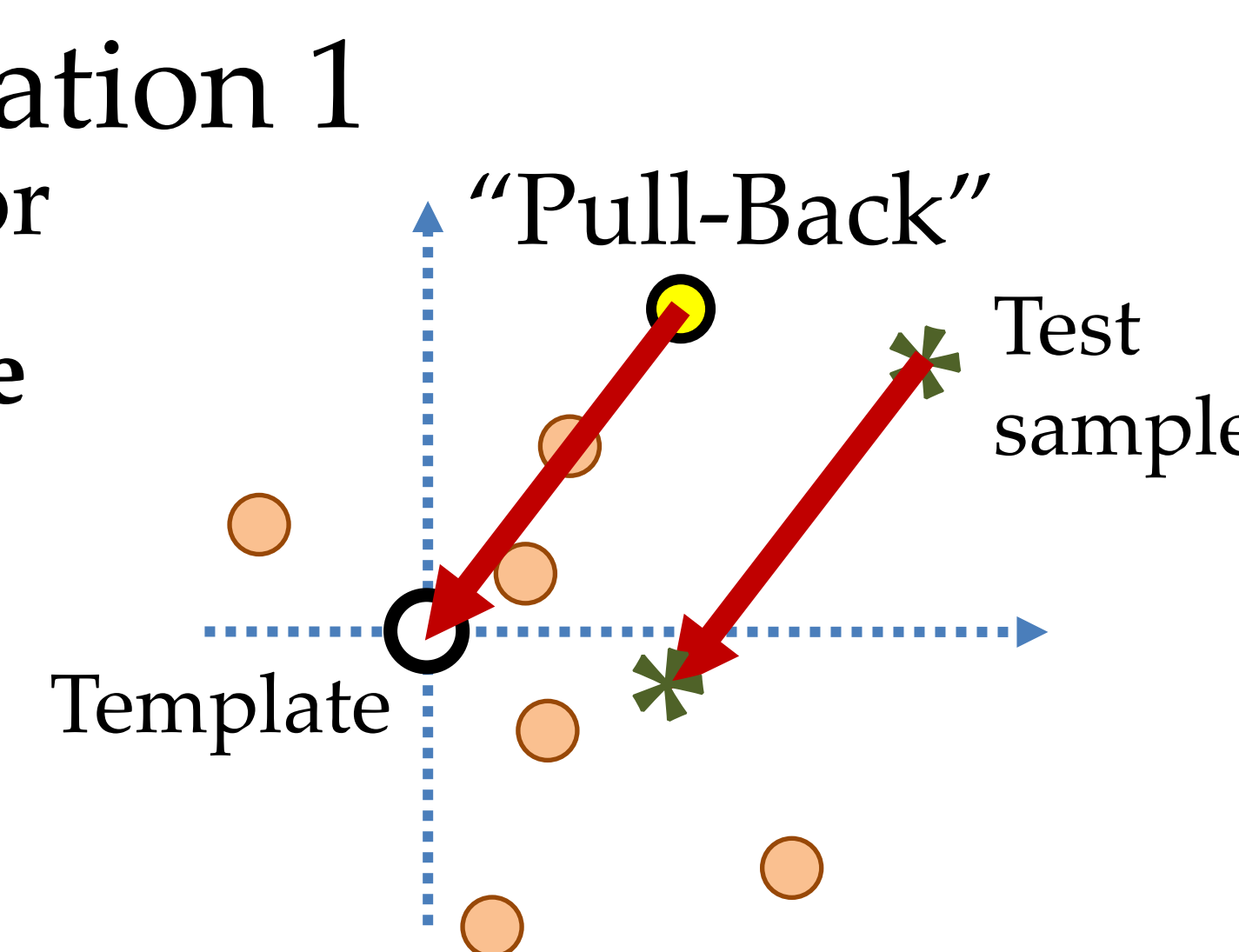
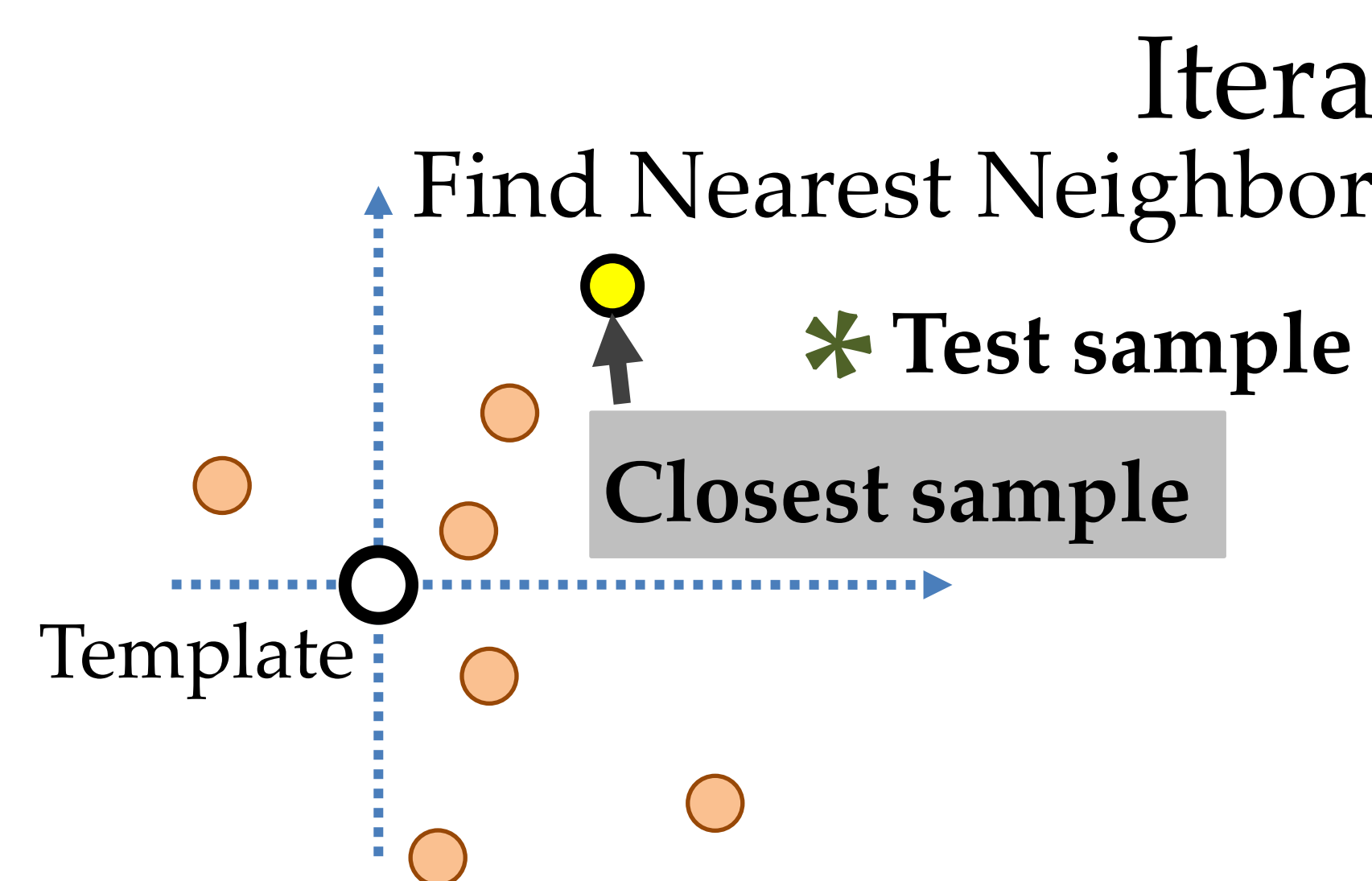
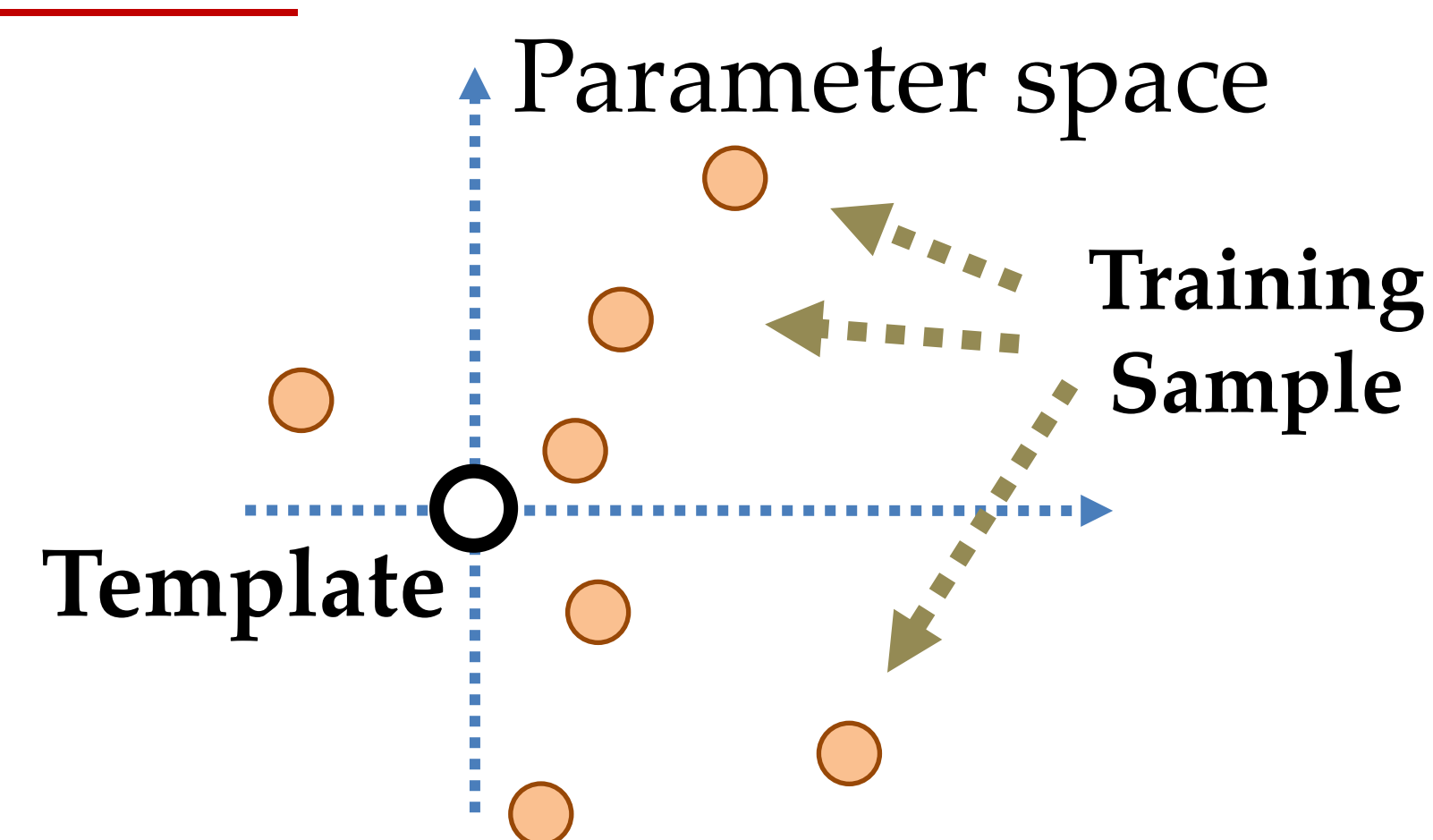
Previous Works	Generative	Discriminative
Method	Optimization	Direct Mapping
Disadvantages	Local minima	Exponential #samples

Contribution

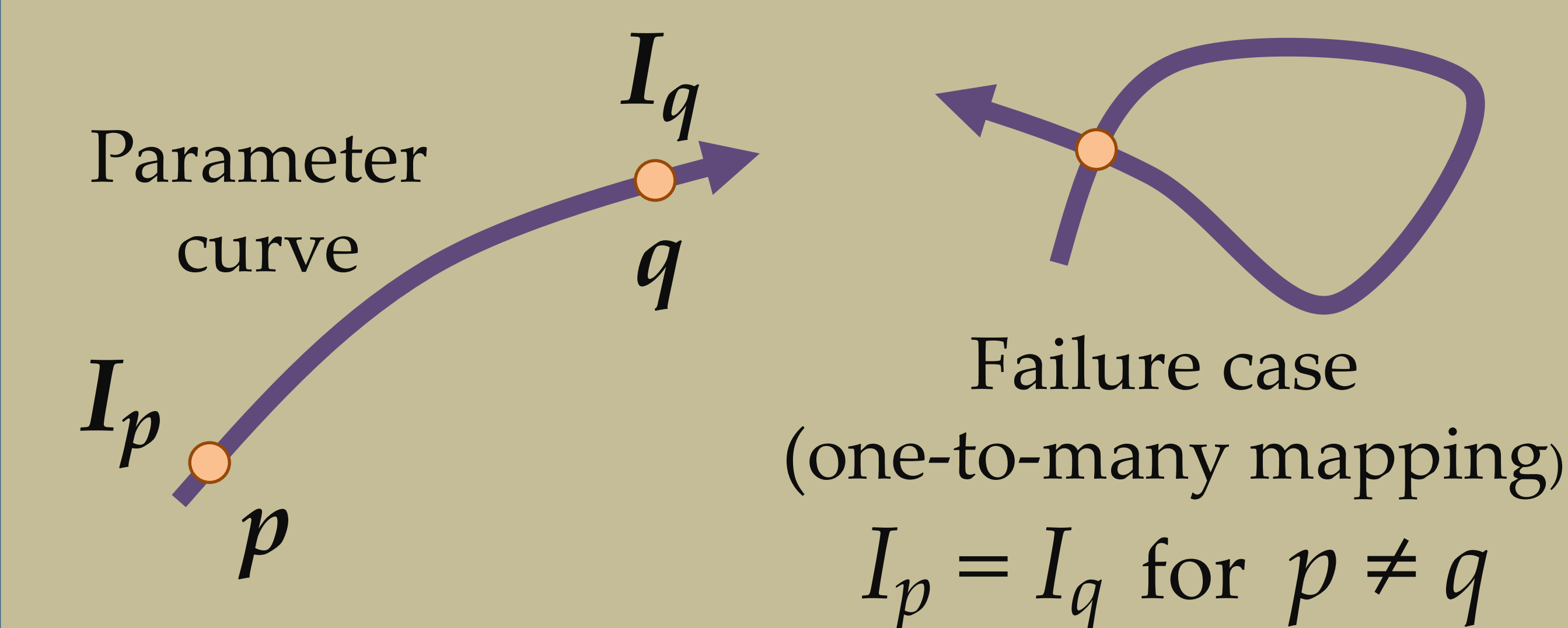
1. Guaranteed worst-case convergence to the **global optimum** using only $O(C^d \log(1/\epsilon))$ samples.
2. Decoupling accuracy $1/\epsilon$ from the dimension d of the parameter space.



The Algorithm



Effectiveness of Nearest Neighbor



Lipchitz Continuity:

$$L_1 \|I_p - I_q\| \leq \|p - q\| \leq L_2 \|I_p - I_q\|$$

The Pull-back Operation

For invertible distortion (e.g. affine):

$$H(I_p, q) = \text{Inv}(I_p, q) = I_{p-q}$$

For non-invertible distortion:

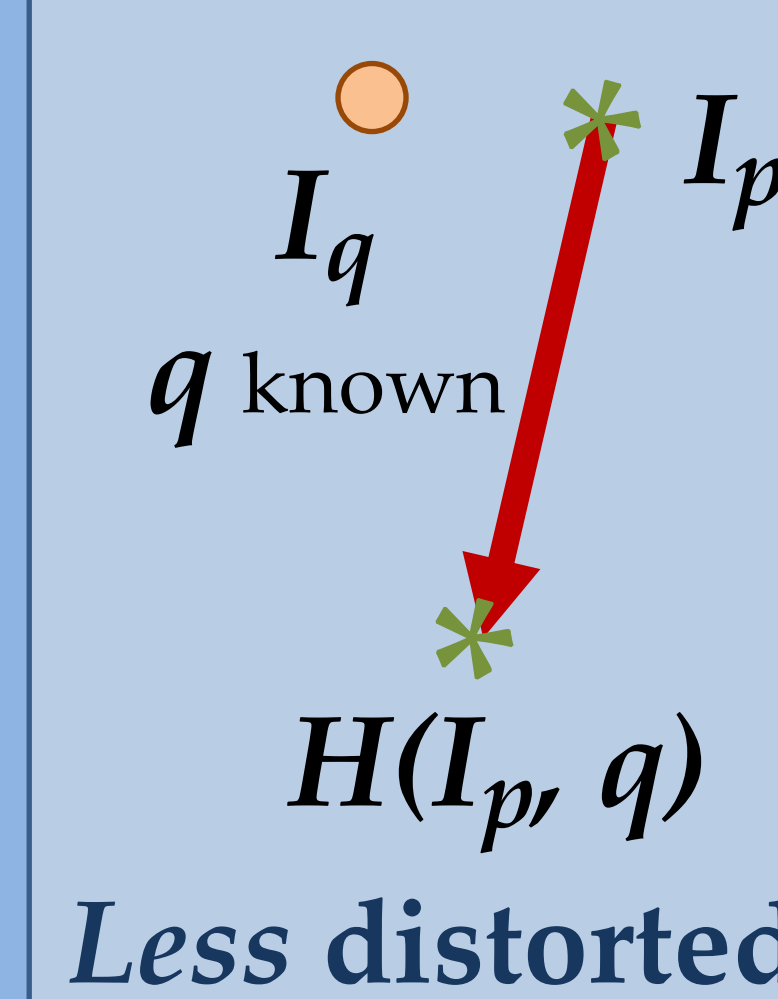
$$\text{In the case of } W(x; p) = x + B(x)p$$

$$\text{We prove } \|I_{p-q} - H(I_p, q)\| \leq R \|p - q\|$$

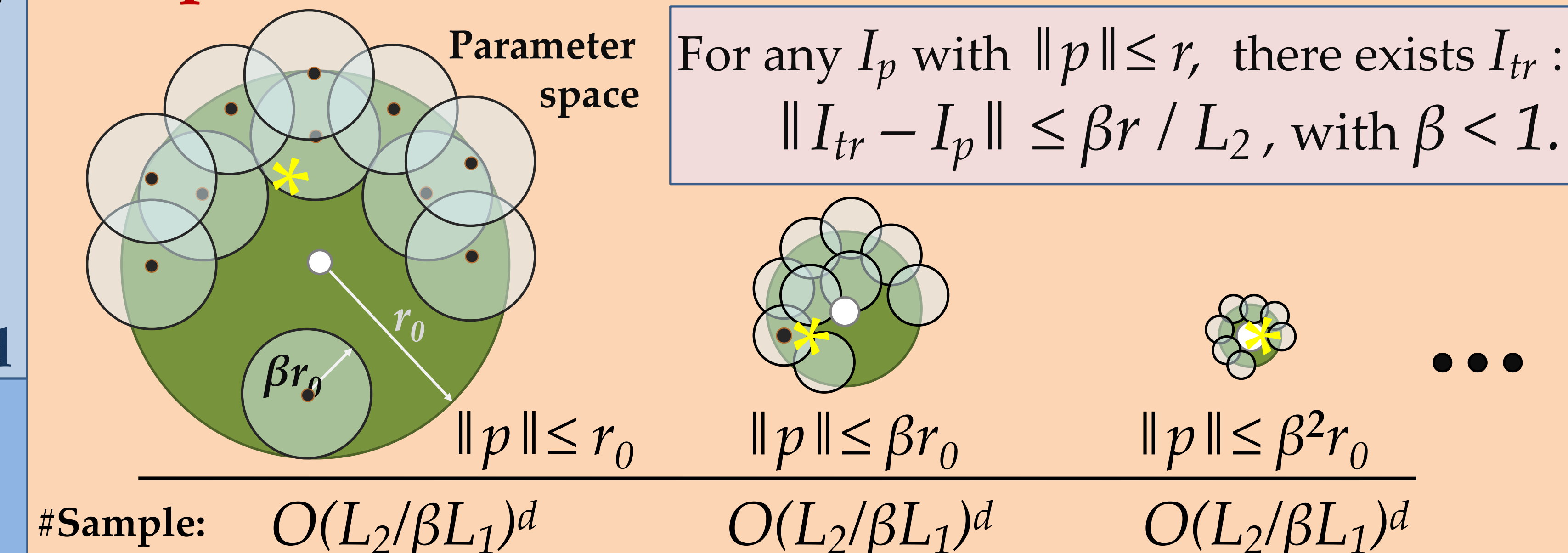
Failure case:

Resampling artifacts.
E.g. Aliasing

A constant related to
 $\max(\|\nabla B(x)\|, \|\nabla T\|)$



Sample Distribution



Total number of samples for accuracy $1/\epsilon$:

$$N(\beta, \epsilon) = O\left[\left(\frac{L_2}{\beta L_1}\right)^d \log_{\beta} \frac{r_0}{\epsilon}\right] = O(C^d \log \frac{1}{\epsilon})$$

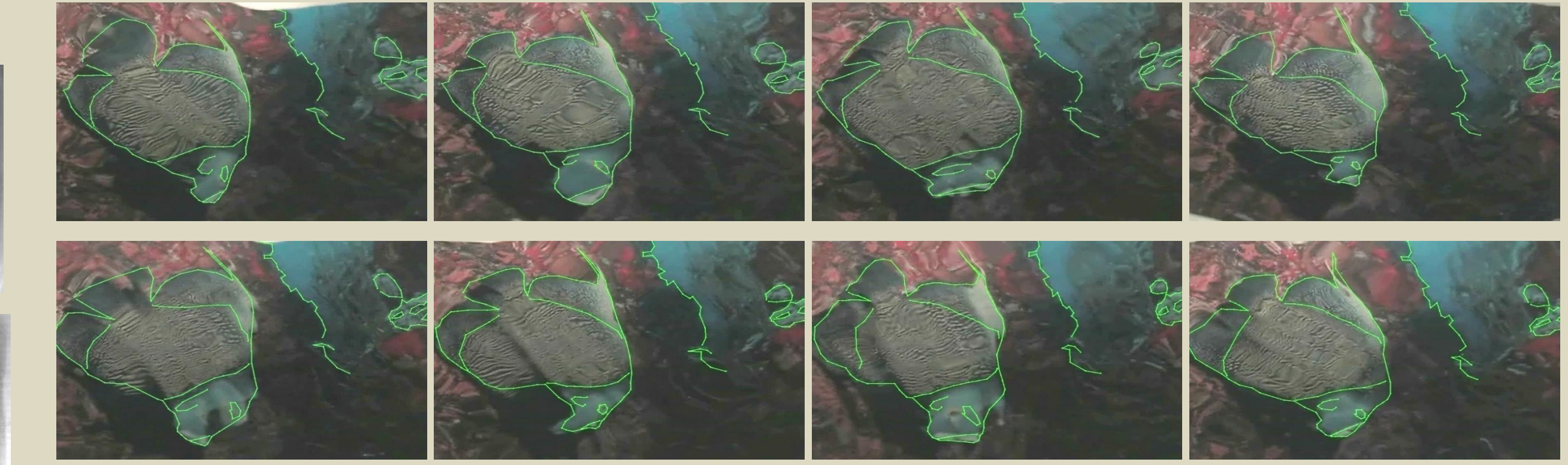
Experimental Result

More results on <http://www.cs.cmu.edu/~yuandong/>

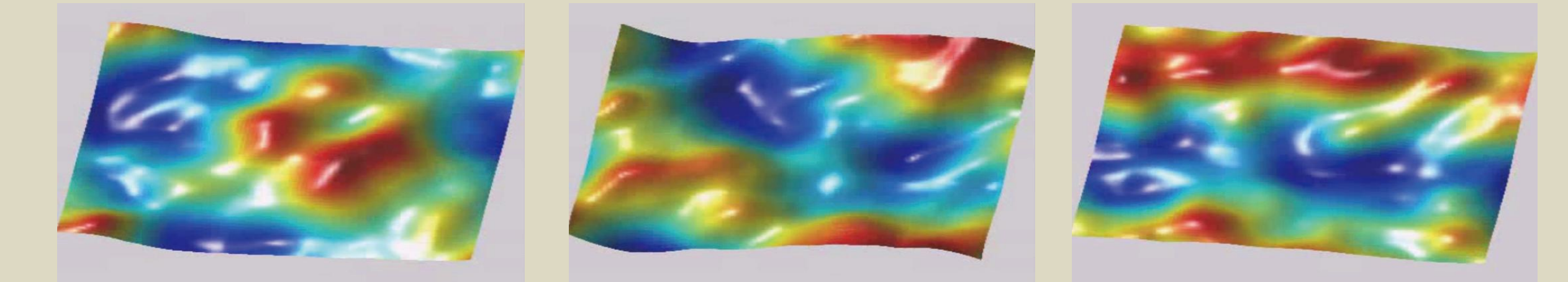
Rectification



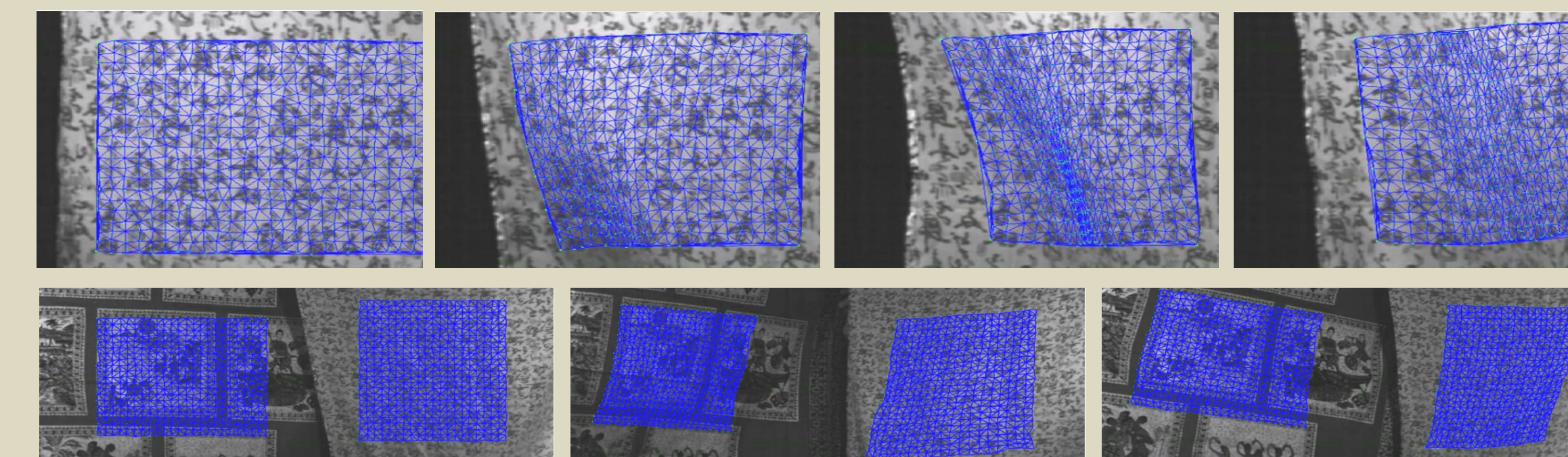
Tracking



Surface Reconstruction



Cloth Deformation



[Data from J.Taylor et.al, CVPR 2010]

Simulation

