Super-Resolution Reconstruction in HAADF STEM

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Outline

Goals and Obstacles

Background and Motivation

Nonlocal-Means Super-resolution reconstruction

Basic Algorithm

Diagnosis algorithm: Fusion + deblurring

Reconstruction algorithm:

NLMdiagnostics + registration + NLM + $\cdots$

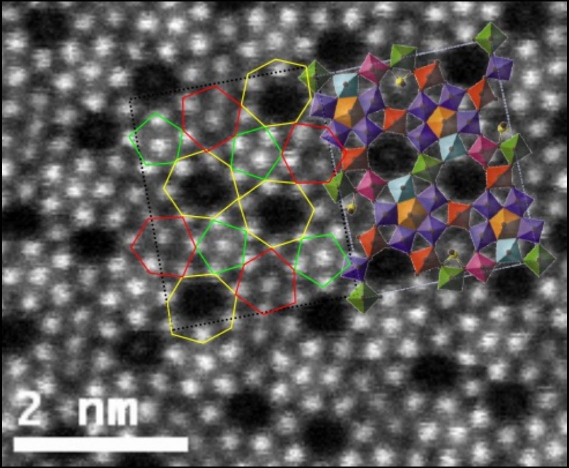
Super-resolution Image Reconstruction

Definition

Technique to obtain, from a sequence of observed multiple signals, a single one with enhanced spatial resolution.

HAADF STEM

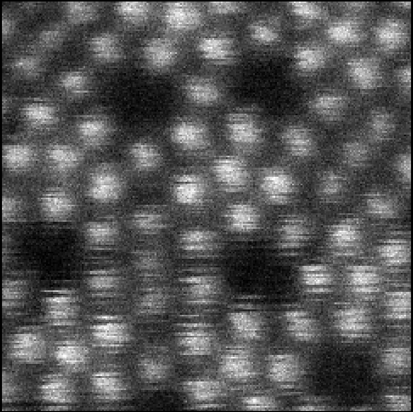
High-**A**ngle **A**nnular **D**ark-**F**ield **S**canning **T**ransmission **E**lectron **M**icroscopy



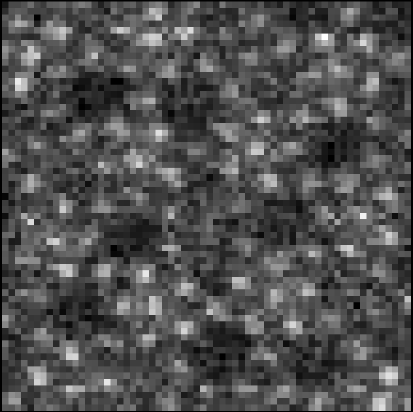
Z-contrast micrograph of a MoVTeNb-oxide M1.

HAADF STEM

Issues: distorsions, noise



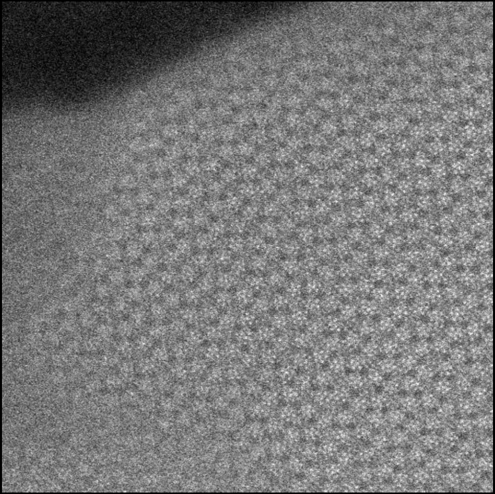
High-dose micrograph (detail)



Low-dose micrograph (detail)

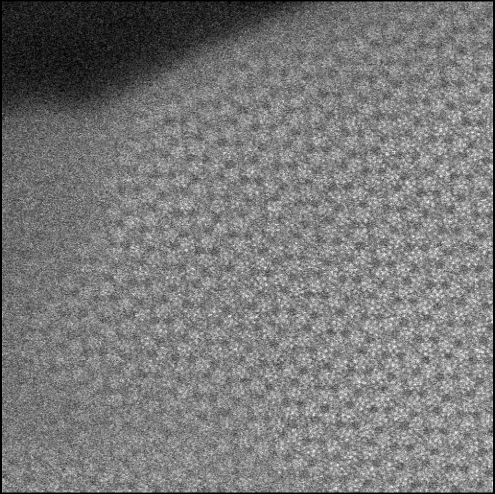
HAADF STEM

Issues: Sample reacting to image acquisition procedure



HAADF STEM

Issues: Sample reacting to image acquisition procedure



HAADF STEM

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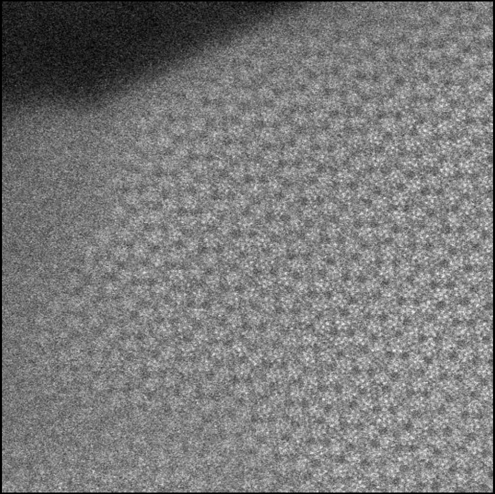

HAADF STEM

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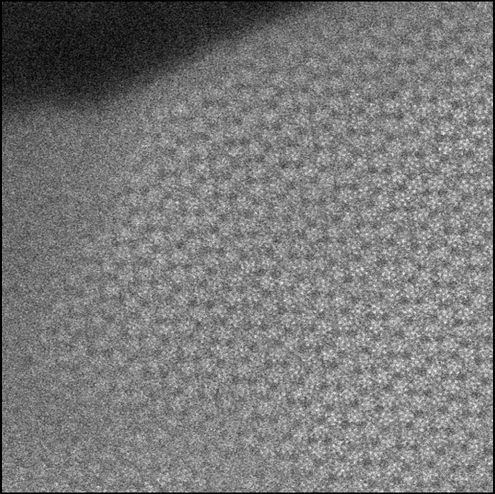
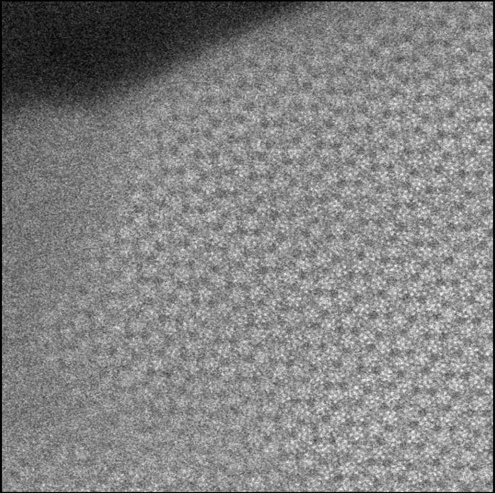


HAADF STEM

Issues: Sample reacting to image acquisition procedure



Super-resolution goal in HAADF-STEM: Summary

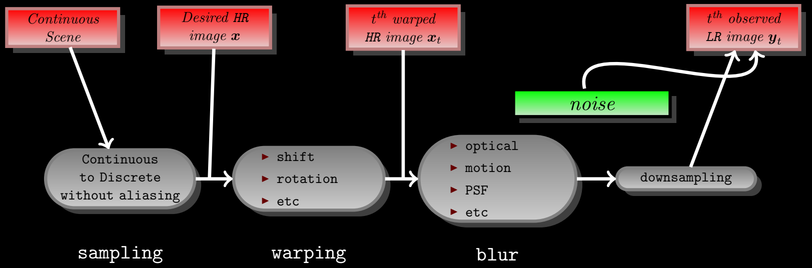
Goal

Obtaining a `HIGH RES` image from a timeseries of low dose `LOW RES` micrographs. Combined energy dose of `LOW RES` timeseries will be lower than equivalent single frame `HIGH RES` output.

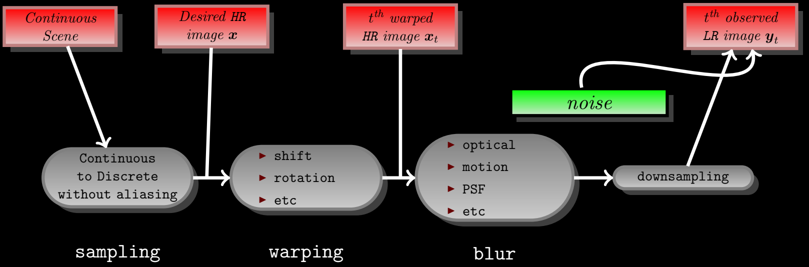
Issues

- Rastering defects produced by external sources.
- Low SNR
- Time-series:
  - Global drift of the sample.
  - Localized jittering of the sample.
  - Occasional change of intensity in consecutive frames.

Observation Model



Observation Model



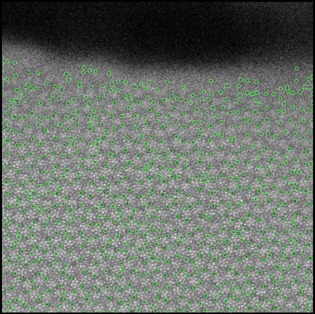
$$\boldsymbol{y}_t = \underbrace{\boldsymbol{D}\boldsymbol{H}_t\boldsymbol{M}_t}_{\boldsymbol{W}_t} \boldsymbol{X} + n_t$$

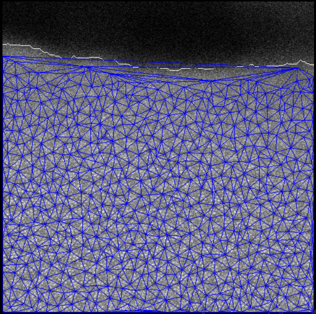
$$\operatorname*{argmin}_{\boldsymbol{X}} \left\{ \sum_{k=1}^{p} \|\boldsymbol{y}_t - \boldsymbol{W}_t X\|^2 + \lambda \operatorname{prior}(X) \right\}$$

Methods based on subpixel motion

Relies on accurate registration methods based on robust motion

- Segmentation
- Multiple object motion
- Occlusions
- Transparency
- …





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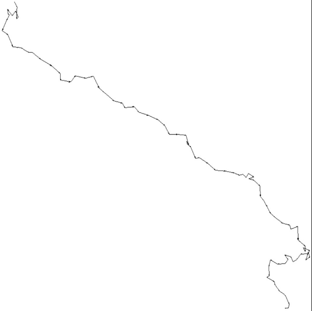
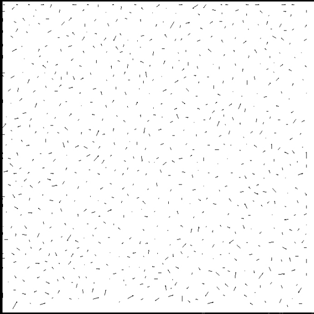
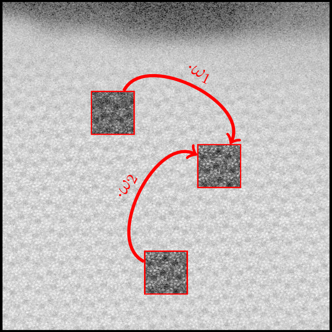




Motionless methods

Relies on patch-average image sequence restoration

- Space-time adaptation
- Moving-window varying size 3D transform-based
- Sparse and redundant representations
- Non-local means
- ...



Blind SR Image Reconstruction

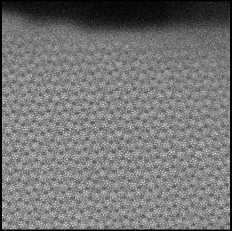
If the blurring processes $\boldsymbol{H}_t$ are unknown, their identification is incorporated to the reconstruction procedure.

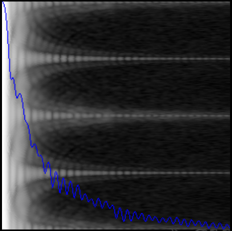
- Blind multichannel algorithms

  Each observed image is a linear combination of the polyphase components of the HR signal.
  —Wirawan et al.'89

- Parametric blur identification and regularization

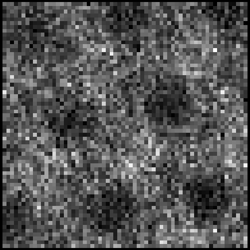
  —Nguyen et al.'01





Nonlocal-means: Pseudocode

Buades, Coll, Morel'05



`source`

`target`

Nonlocal-means: Pseudocode

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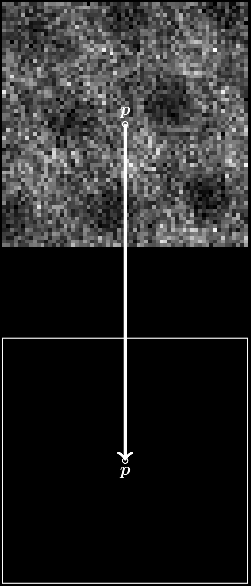
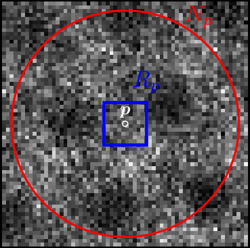
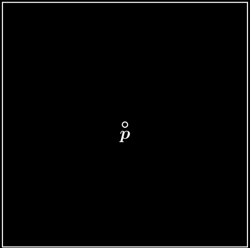



```
For each pixel p {
```

Nonlocal-means: Pseudocode

Buades, Coll, Morel'05



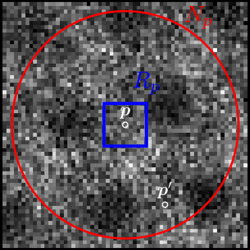


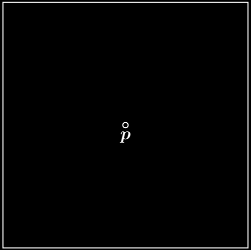
For each pixel p {

- Take neighborhood centered in p: N_p
- Take patch centered in p: R_p

Nonlocal-means: Pseudocode

Buades, Coll, Morel'05



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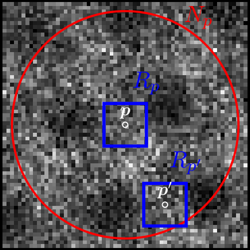
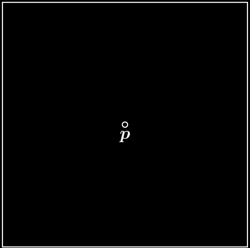


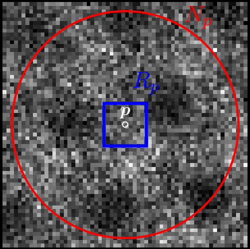
e.g.
$\mathrm{dist}(p, p') = \|R_p - R_{p'}\|_2^2$




```
For each pixel p {
• Take neighborhood centered in p: N_p
• Take patch centered in p: R_p
For each pixel p' in N_p {
    • Compute a distance dist(p,p')
        between R_p and R_p'.
    • Compute weight w(p,p') from dist(p,p')
    • stack = Σ_{p'∈N_p} w(p,p') * source(p');
    • totalweight = Σ_{p'∈N_p} w(p, p');
}
```

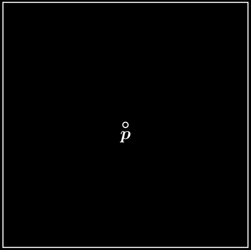
Nonlocal-means: Pseudocode

Buades, Coll, Morel'05



e.g.

$$w(p,p') = \exp\left\{-\frac{\mathrm{dist}(p,p')}{2\sigma^2}\right\}$$



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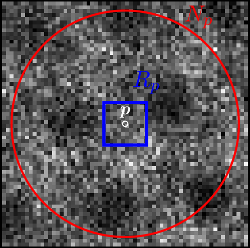

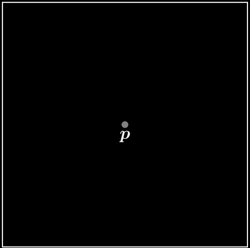

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}

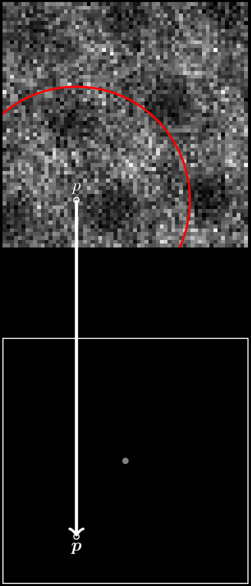
- Compute the restored value (normalization)

$$\text{target(p)} = \frac{\text{stack}}{\text{totalweight}};$$

}

Nonlocal-means: Pseudocode

Buades, Coll, Morel'05



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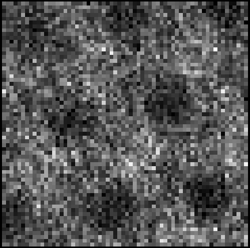

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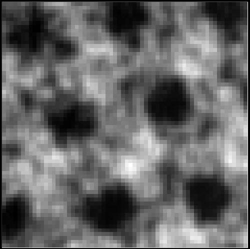

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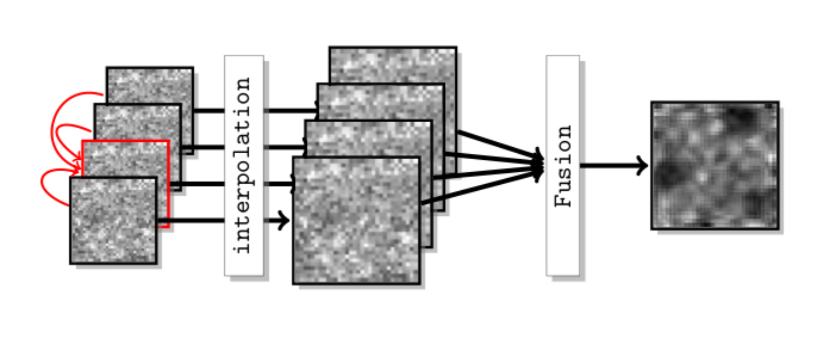
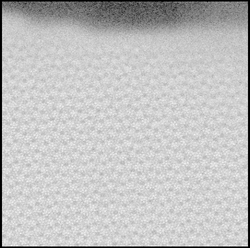
Nonlocal-Means Super-resolution reconstruction

Protter, Elad, Takeda, Milanfar'09

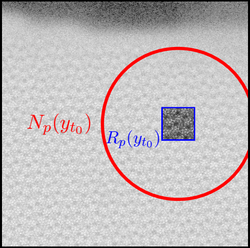


Fusion

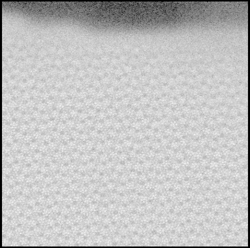
Normalization



$\boldsymbol{y}_{t_1}$



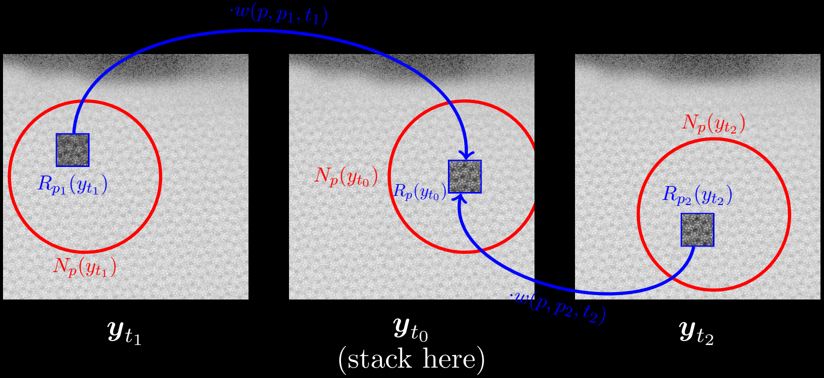
$\boldsymbol{y}_{t_0}$
(stack here)



$\boldsymbol{y}_{t_2}$

Fusion

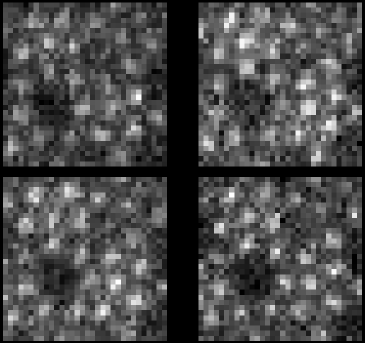
Normalization

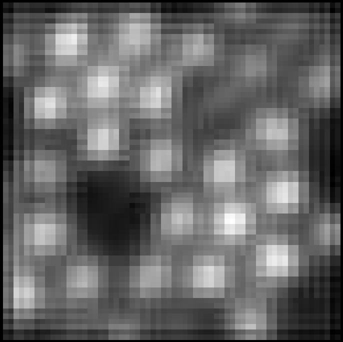


$$\mathtt{target}(p, t_0) = \frac{\sum_t \sum_{p' \in N_p(y_t)} w(p, p', t) R_{p'}(y_t)}{\sum_t \sum_{p' \in N_p(y_t)} w(p, p', t)}$$

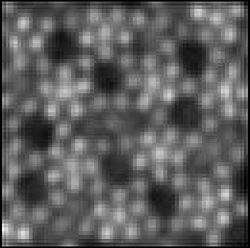
Fusion

Normalization example



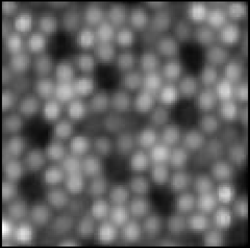


Deblurring normalized sequences

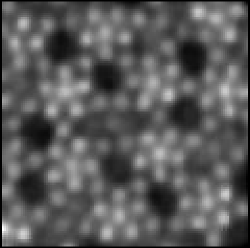


normalization

$Z_{t_0} = \texttt{target}(\cdot, t_0)$



Deblurring H_1

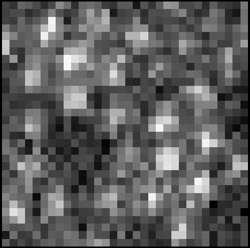


Deblurring H_2

$$X_{t_0} = \underset{X}{\operatorname{argmin}} \left\{ \|Z_{t_0} - \boldsymbol{H}_k X\|_2^2 + \lambda \, \text{prior}(X) \right\}$$

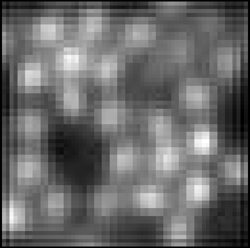
usually, prior(X) is one of $\|X\|_0$, $\|X\|_1$, $\|\nabla X\|_2$, etc

Reconstruction algorithm



Given a time-series of micrographs $\{y_t\}_{t=1,\ldots,N}$

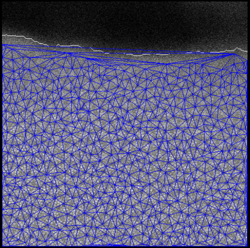
Reconstruction algorithm



Given a time-series of micrographs $\{y_t\}_{t=1,\ldots,N}$

1. "simple" diagnosis NLM $\rightarrow \{Z_t\}_{t=1,\ldots,N}$

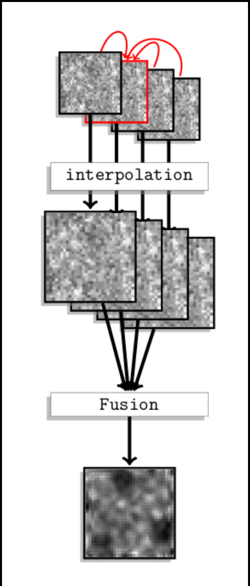
Reconstruction algorithm



Given a time-series of micrographs $\{y_t\}_{t=1,\dots,N}$

1. "simple" diagnosis NLM $\rightarrow \{Z_t\}_{t=1,\dots,N}$
2. Use diagnosis time-series to:
   - Feature tracking to register $\{y_t\}$.
   - Localized alignment.
   - Improve **distance** notion (factor-out local distorsions).

Reconstruction algorithm



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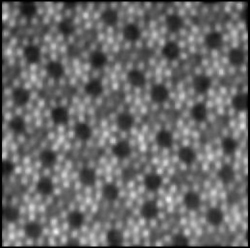
3. Reiterate NLM.

Reconstruction algorithm



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3. Reiterate NLM.
4. Deblurring.

Punch line

Thank you!