An overview of Coded Aperture techniques for image super-resolution, and relevant performance metrics

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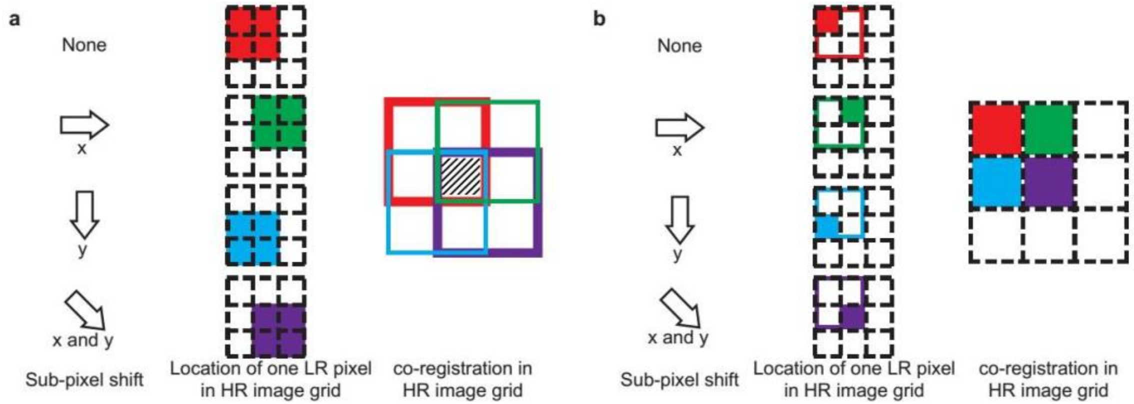
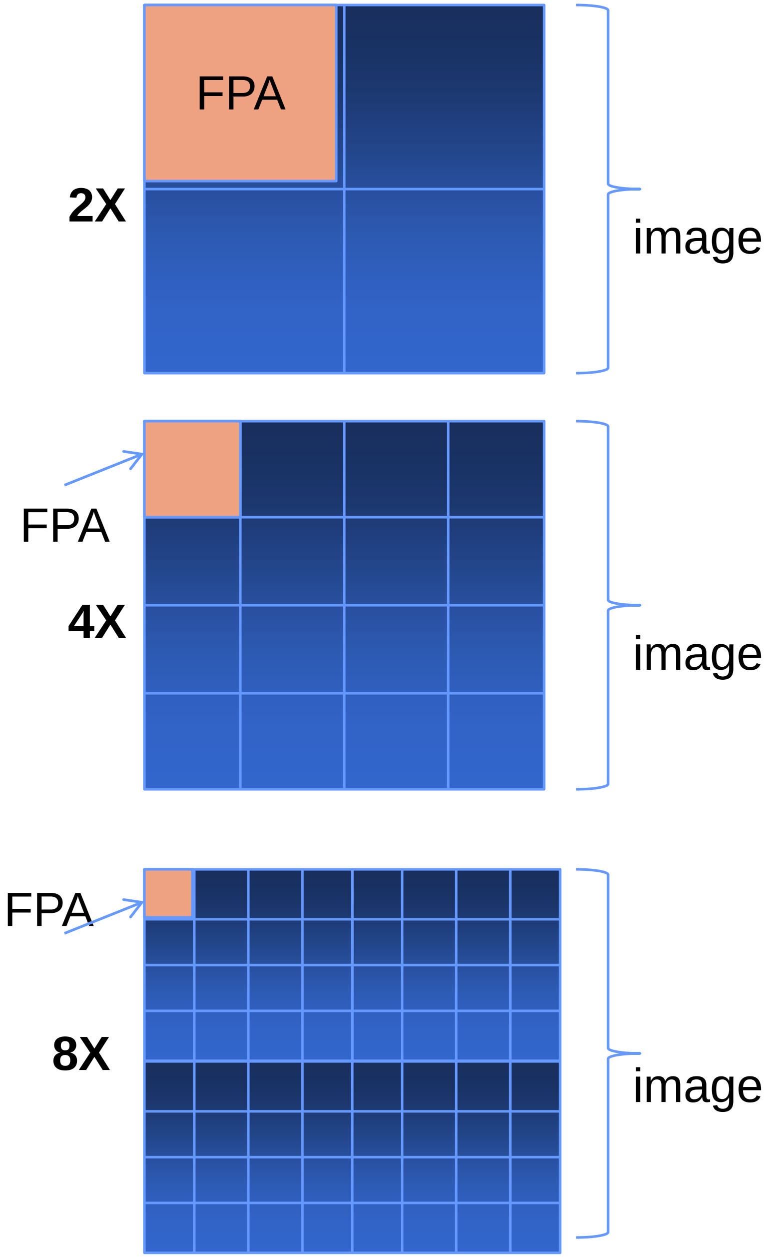
Goal for resolution improvement using micro-scanning

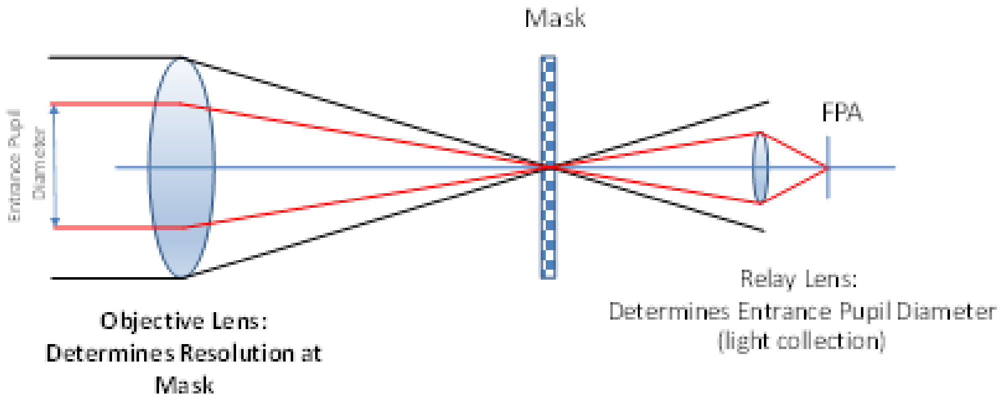


Sun et. al. Infrared single pixel imaging utilizing micro-scanning

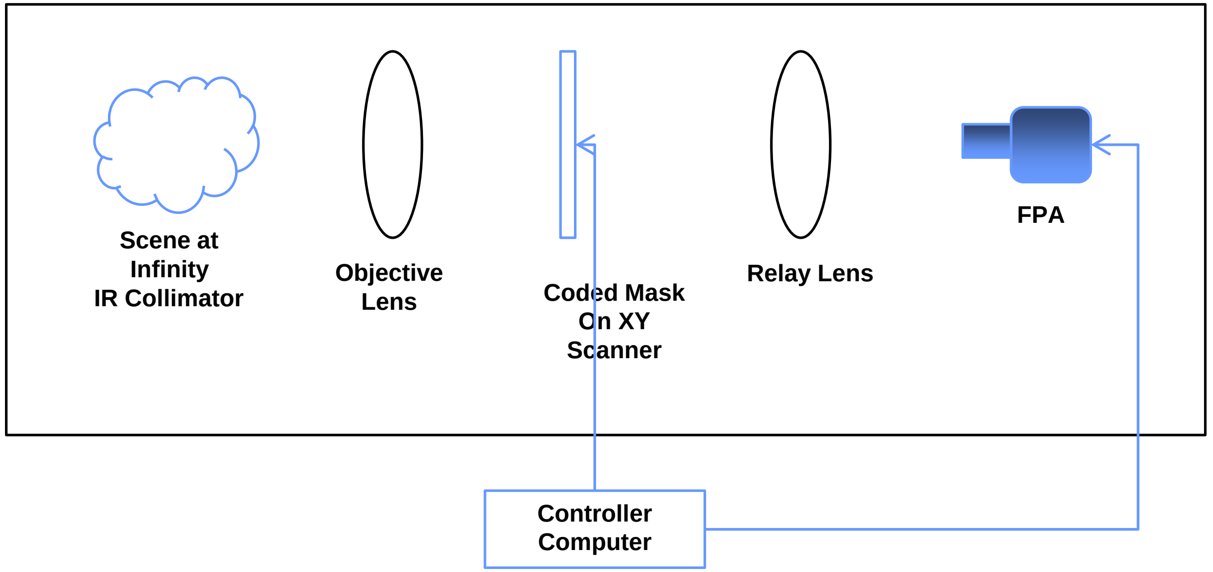


- Traditional digital super-resolution using dither achieves around 2.5X
- Coding can dramatically increase super-resolution gain
  - Our goal is to achieve 8X (1:64) increase in resolution
- Demonstrate super-resolution using simple implementation of codes

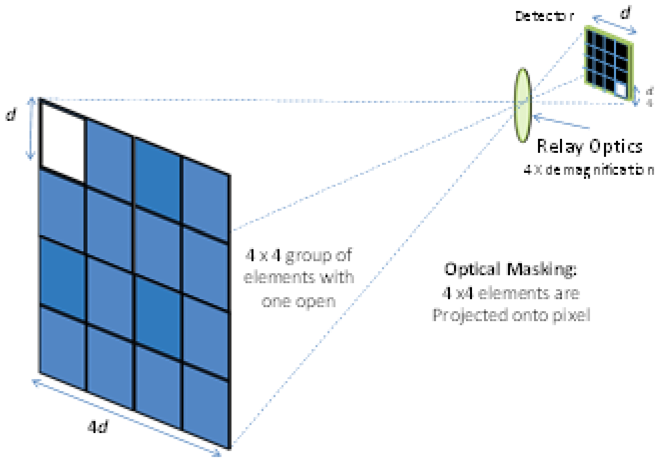
Image Coding and Sensing Concept



The image formed at the mask is coded at the desired higher resolution, and re-imaged with demagnification on a low resolution FPA



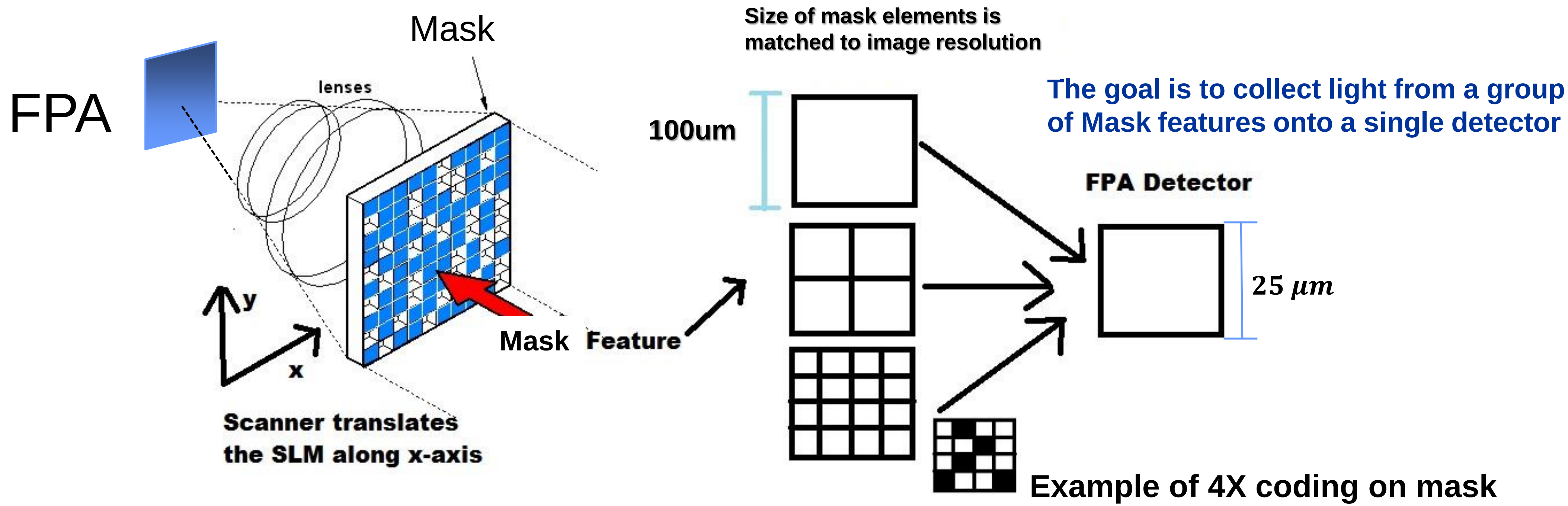
The FPA captures a coded frame of data as the mask steps across the scene on a x-y scanning stage.



The re-imager maps a group of mask elements onto a single detector. As the mask moves, the pattern of open and closed elements changes.

- **Motivated by the published works of other teams that have already demonstrated sliding mask strategies for computational imaging**
  - Llull et. al “Coded aperture compressive temporal imaging”

Relation between Mask features and FPA

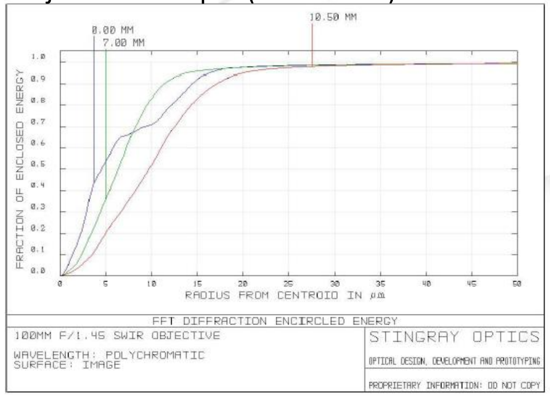


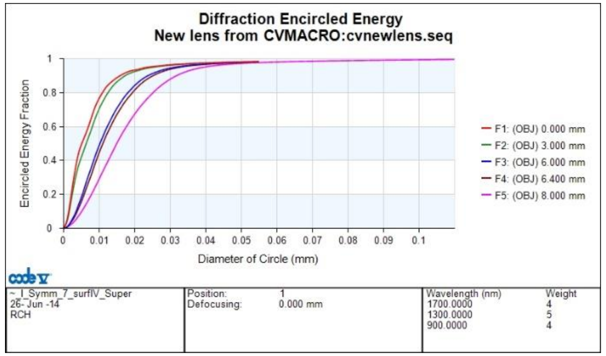
- **Scanner moves in increments of 5 microns in "x" direction.**
- **The relay imager provides 1:4 demagnification from the Mask to the FPA**
  - **a 100μm x 100μm area on the mask is imaged onto $25\mu m \times 25\ \mu m$ area on the FPA**

- **A 4X resolution improvement is achieved by using 25μm x 25μm mask elements**
- **A 10X ratio is achieved by using 10μm x 10μm mask elements**

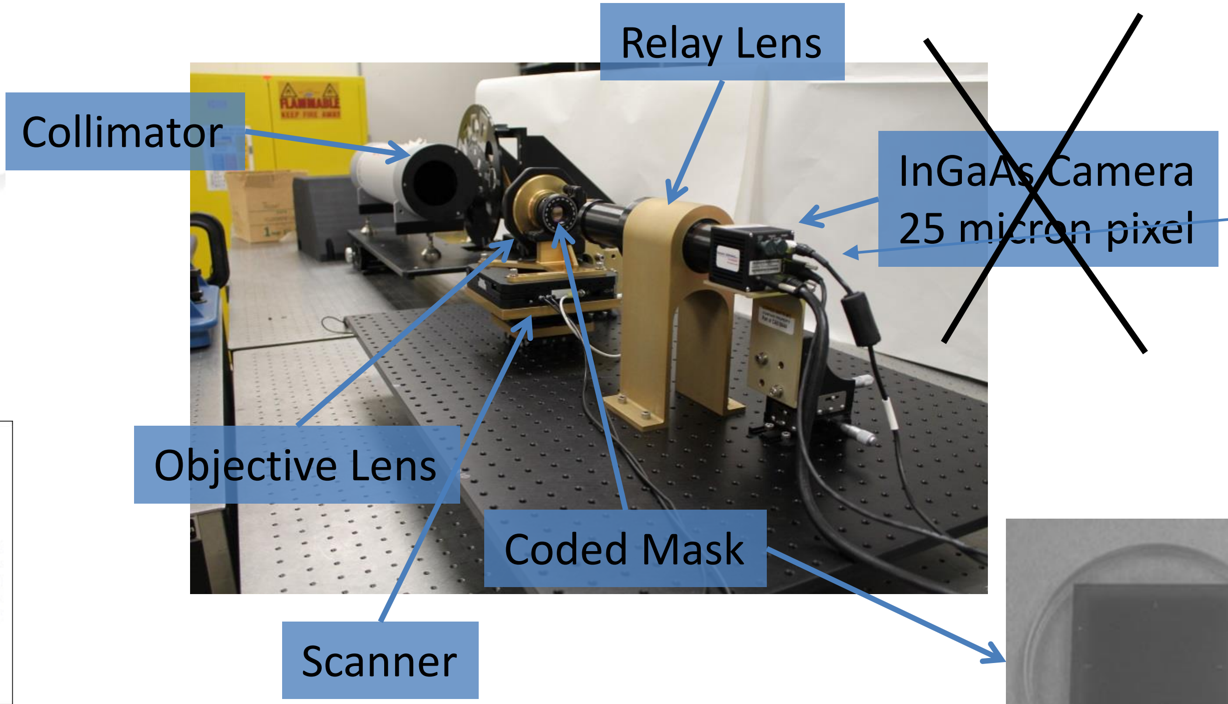
Laboratory Set up for 8X reconstruction

Objective Blur Spot (25 microns)

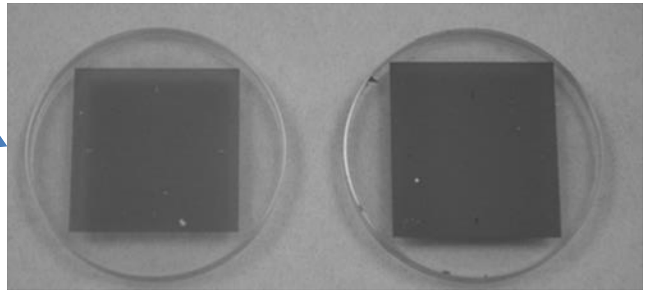




Relay Blur Spot (25 microns)



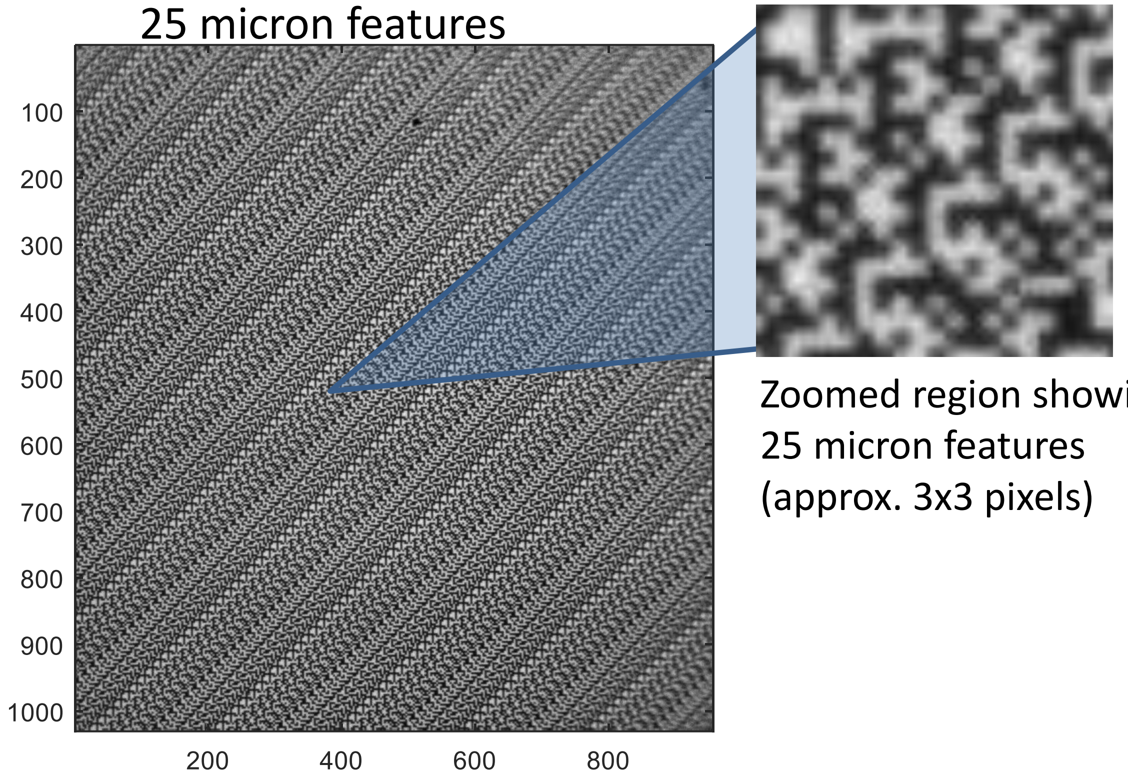
Allied Vision
2.2 micron
2592 x 1944 pixel
12-bits
Software binning



- A high resolution camera was used to capture images of the mask as viewed through the re-imager
  - Eliminated registration issues.
- Towards this end, the 25 micron SWIR camera was replaced with 2.2 micron visible band camera
  - The lenses were not changed. Spectral filters and apertures stops were used to ensure optical resolution.
  - 10 micron blur spot at the mask is matched by 10 micron mask features
  - Re-imager with 4X demagnification maps each mask feature to 2.5 micron on the FPA. This can be resolved using the 2.2 micron pixels.

Images of Masks as viewed through the re-imager.

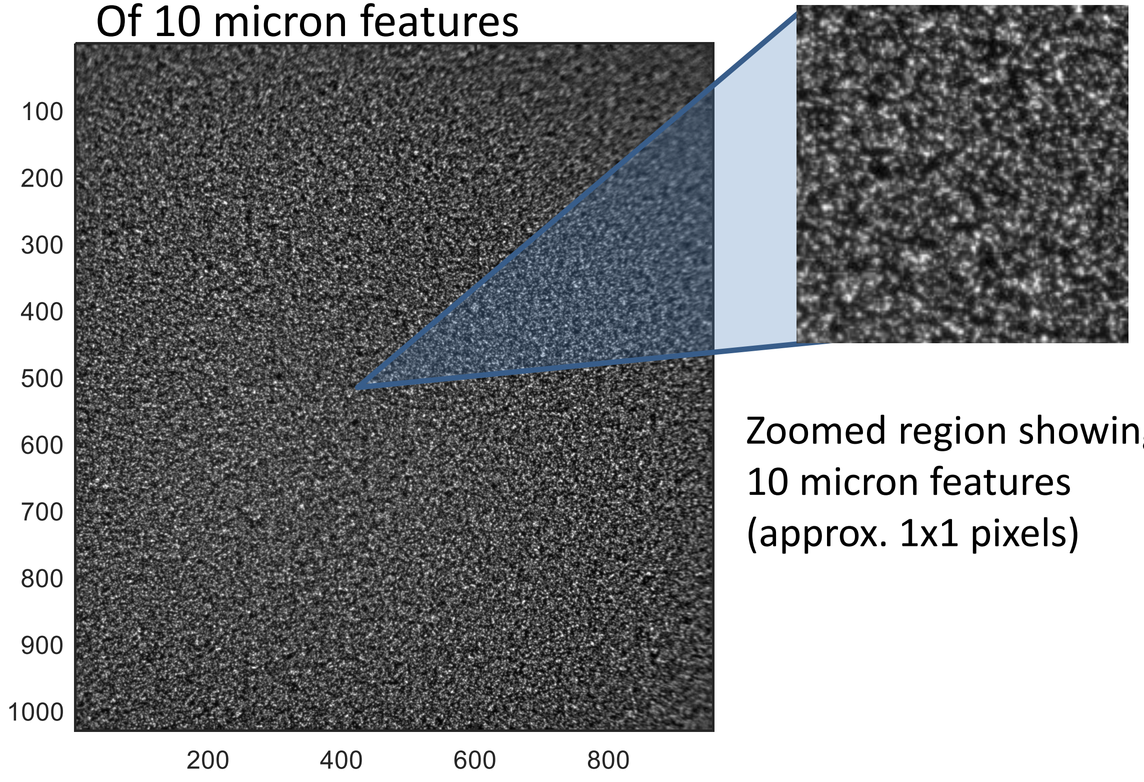
Periodic pattern of
25 micron features



Zoomed region showing
25 micron features
(approx. 3x3 pixels)

1:4 mask

Random pattern (40% open)
Of 10 micron features



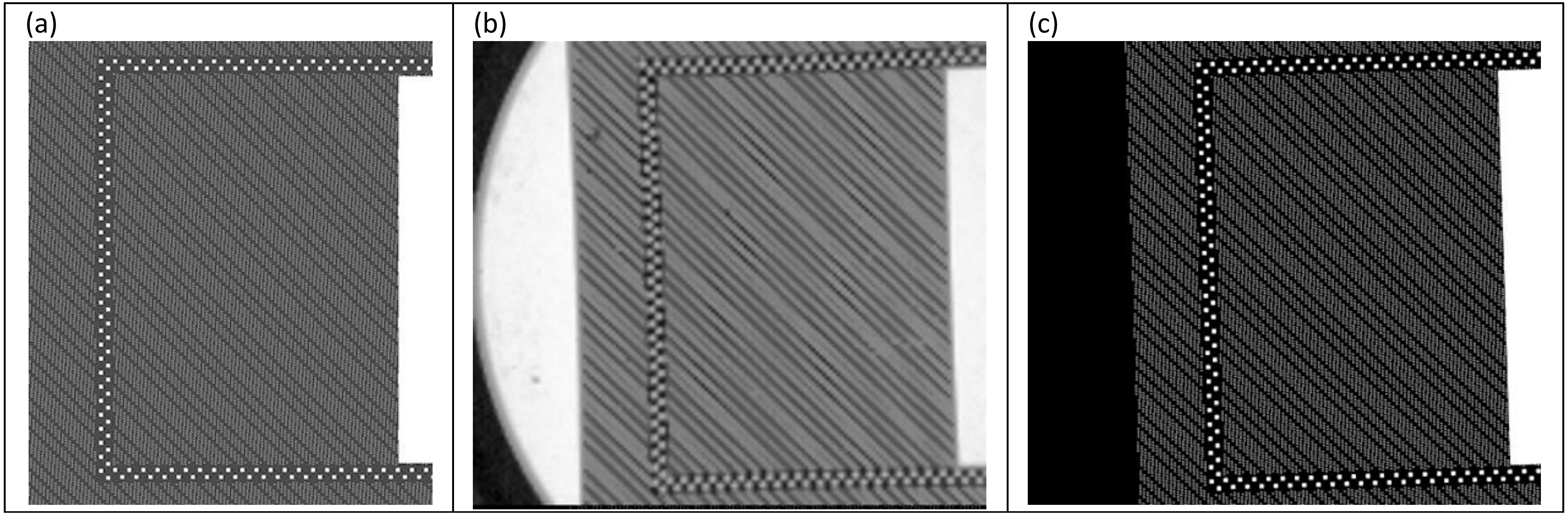
Zoomed region showing
10 micron features
(approx. 1x1 pixels)

1:10 mask

- The high-resolution (1:10) mask has 10x10 micron elements that are resolved as 1x1-pixel features
  - This mask encodes the image at the native resolution of the FPA
- The Low-resolution (1:4) mask has 25x25 micron elements that are resolved as 3x3-pixel features

Mask Registration

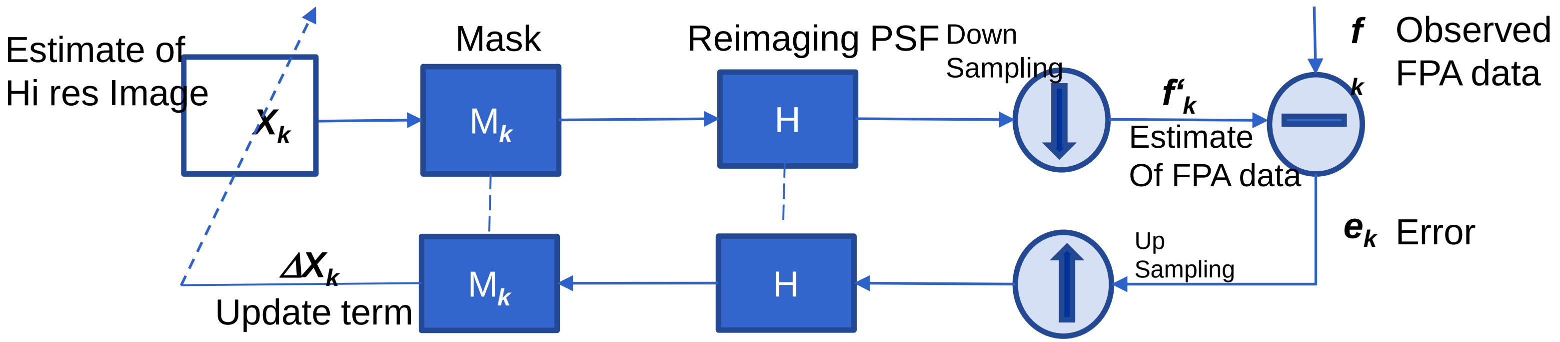
(a) (b) (c)



- It is critical for the ideal mask pattern to be registered to the mask as implemented in the system.
- The ideal mask pattern is shown in (a) and its image as observed through the reimager is shown (b). The result of transforming the ideal pattern so that it matches the observed image is shown in (c), and is used as the function $c_k(m, n)$ for image reconstruction.

Reconstruction algorithm – Gradient Descent

Computationally simple but iterative approach



Estimated FPA data: $f'_k = HM_k x_k$

Square Error: $|e_k|^2 = |HM_k x_k - f_k|^2$

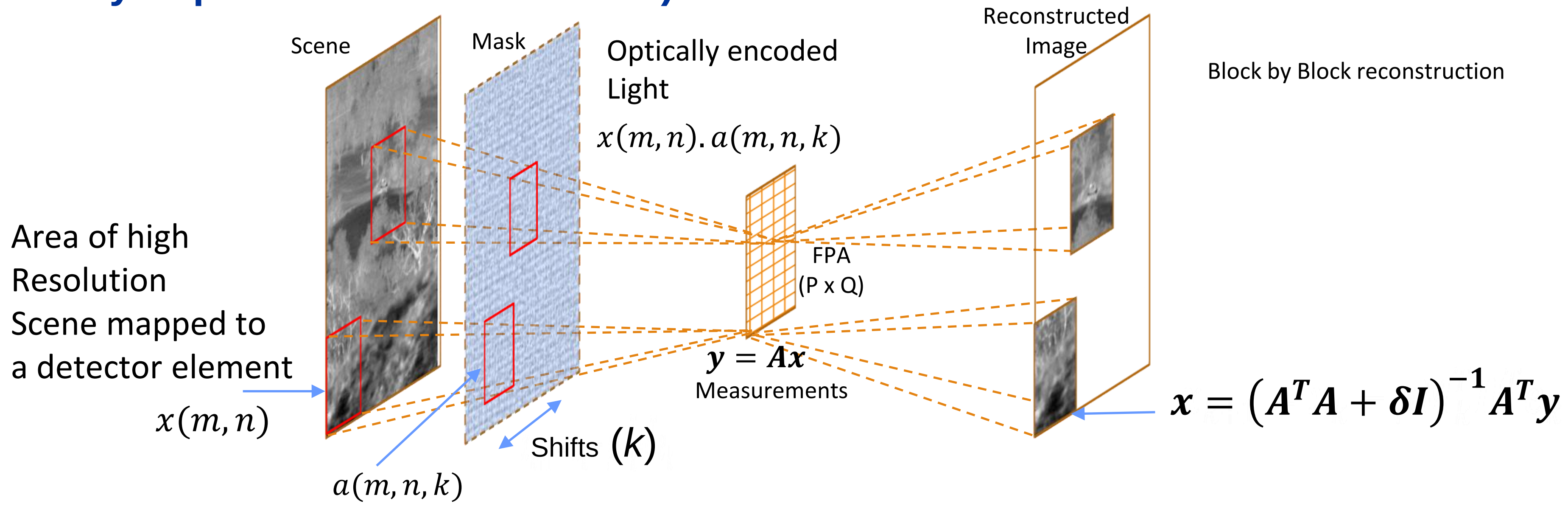
Gradient: $\nabla_x |e_k|^2 = M_k^T H^T e_k$

Update Rule: $x_{k+1} = x_k - \mu M_k^T H^T e_k$

- **In 2015, we described an adaptive (gradient descent) reconstruction algorithm.**
  - **Iteratively learns the least mean square (LMS) error solution with each measurement**
  - **Treats entire scene as a continuous function**
  - **Numerically very straightforward and easy to implement**
- **In 2016, we also explored a closed form “least squares” estimator for block-wise reconstruction of the image.**

Reconstruction Algorithm – Blockwise Least Squares

(Computationally Expensive but closed form)



- **Assume that the FPA has P X Q elements**
- **The mask and the scene are divided into P X Q blocks, each of size MxN**
- **The output at the detector element in row p, column q is given by** $y(k) = \sum_{m=1}^{M} \sum_{n=1}^{N} a(m,n,k)x(m,n)$
  - **This can be written in vector notation as** $y(k) = \boldsymbol{a}_k^T \boldsymbol{x}$**,**
    - $\boldsymbol{a}_k^T$ **and** $\boldsymbol{x}$ **are obtained by lexicographically reordering** $a(m,n,k)$ **and** $x(m,n)$
- **A series of measured values y** $= [y(1) \quad y(2) \quad \ldots \quad y(N)]^{\boldsymbol{T}}$ **are obtained as the mask moves.**
  - **Defining** $A = [\boldsymbol{a}_1 \quad \boldsymbol{a}_2 \quad \ldots \quad \boldsymbol{a}_K]$**, the measurement is given by** $\boldsymbol{y} = \boldsymbol{Ax}$
- **To reconstruct a block of the image, we** $\boldsymbol{minimize}\ |\boldsymbol{y} - \boldsymbol{Ax}|^2 + \boldsymbol{\delta}|\boldsymbol{x}|^2$ (Tikonov Regularization)
- **The solution is given by** $\boldsymbol{x} = \left(\boldsymbol{A^T A} + \boldsymbol{\delta I}\right)^{-1} \boldsymbol{A^T y}$

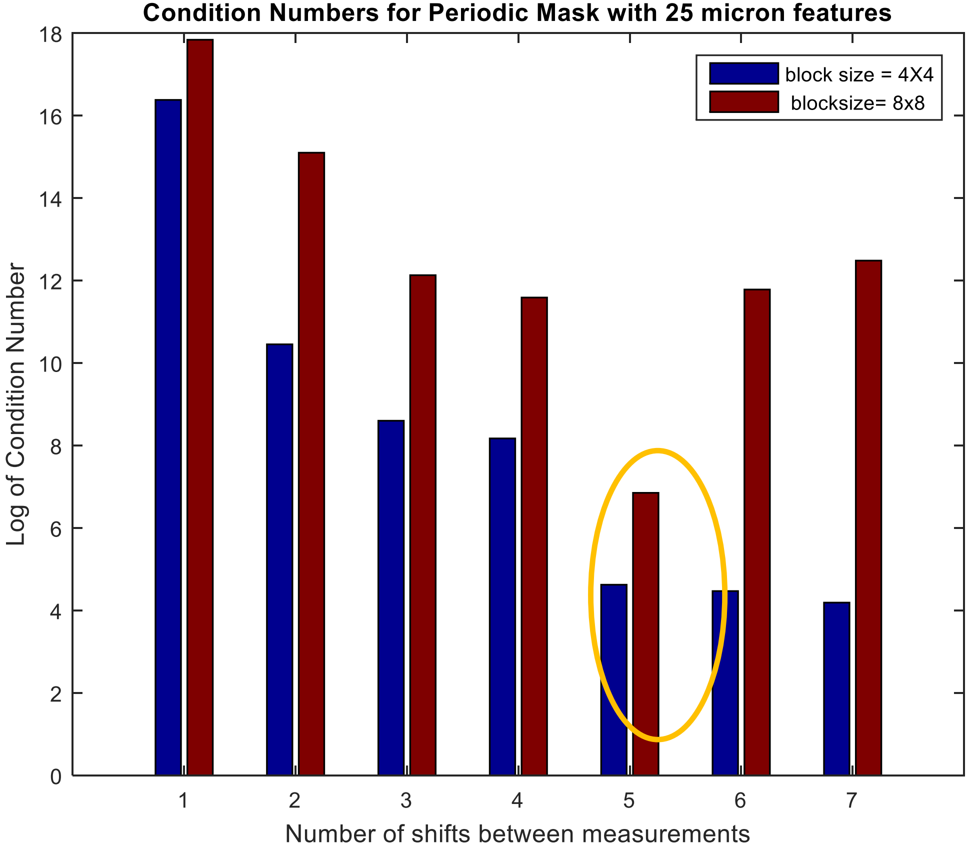
Photon Constraint

- **Consider the L1 norm of the columns of the measurement matrix:**

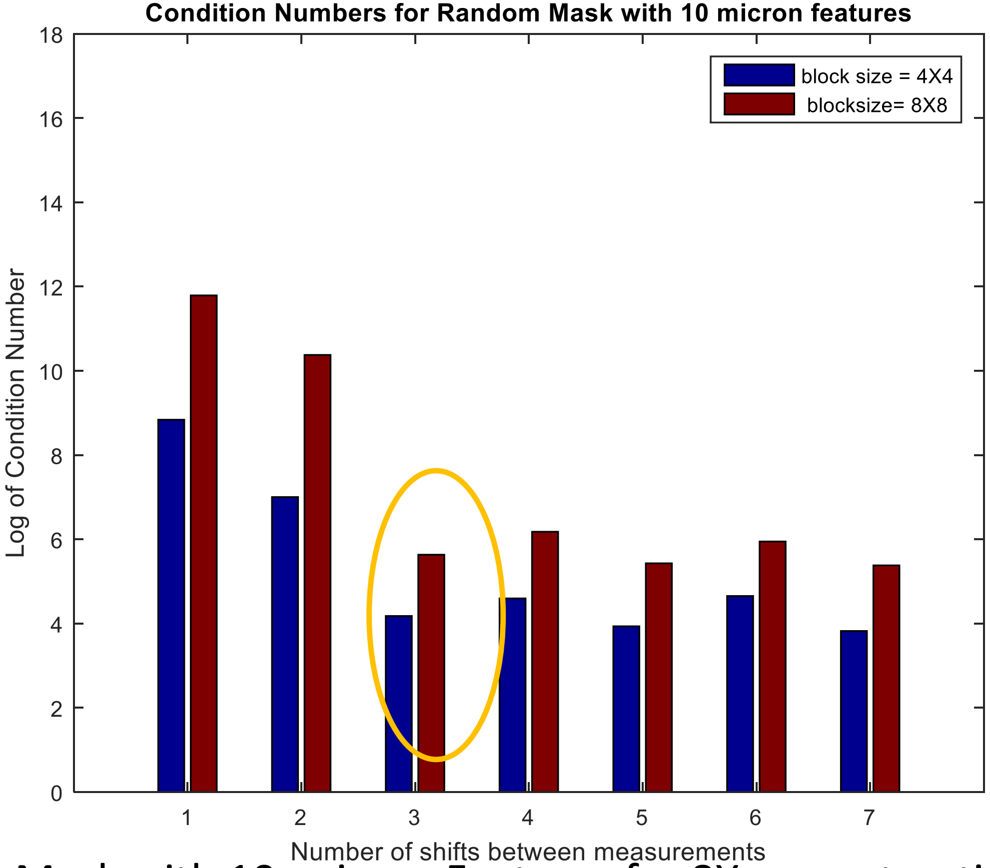
$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_K \end{bmatrix} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,NM} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,NM} \\ \vdots & \vdots & \ddots & \vdots \\ a_{K,1} & a_{K,1} & \cdots & a_{K,NM} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{NM} \end{bmatrix}$$

- The constraint $\max\left\{\sum_{k=1}^{K} \left|a_{k,j}\right|,\ j = 1{:}\,NM\right\} = 1$ ensures that the matrix ***A*** represents measurements made with finite resources.
- An example of the effect of the photon constraint on reconstruction results will be shown later.

Condition Number Depends on Feature size and Shifts



Mask with 25 micron Features for 4X reconstruction

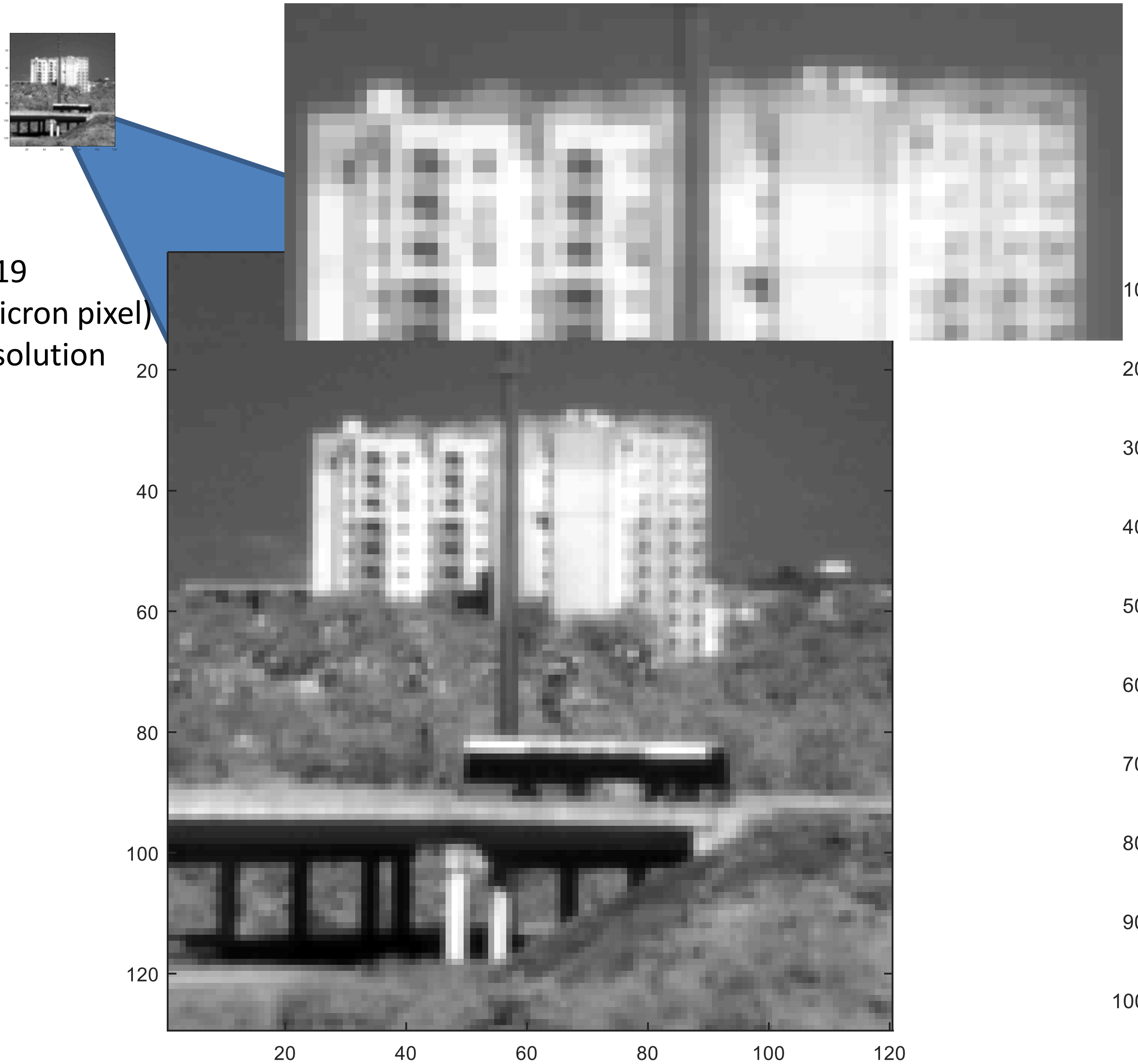


Mask with 10 micron Features for 8X reconstruction

- The scanner allows the mask to be moved in steps of 5 microns between measurements
- The random mask with 10 micron features produces measurement matrices with smaller condition number, than the periodic mask with 25 micron features.
- The condition number is also smaller for a block size of 4x4,
- The mask with 25 micron features should shift by 5 steps between measurements, while 3 steps between measurements is sufficient for the mask with 10 micron features.

Scene at Low and High Resolution

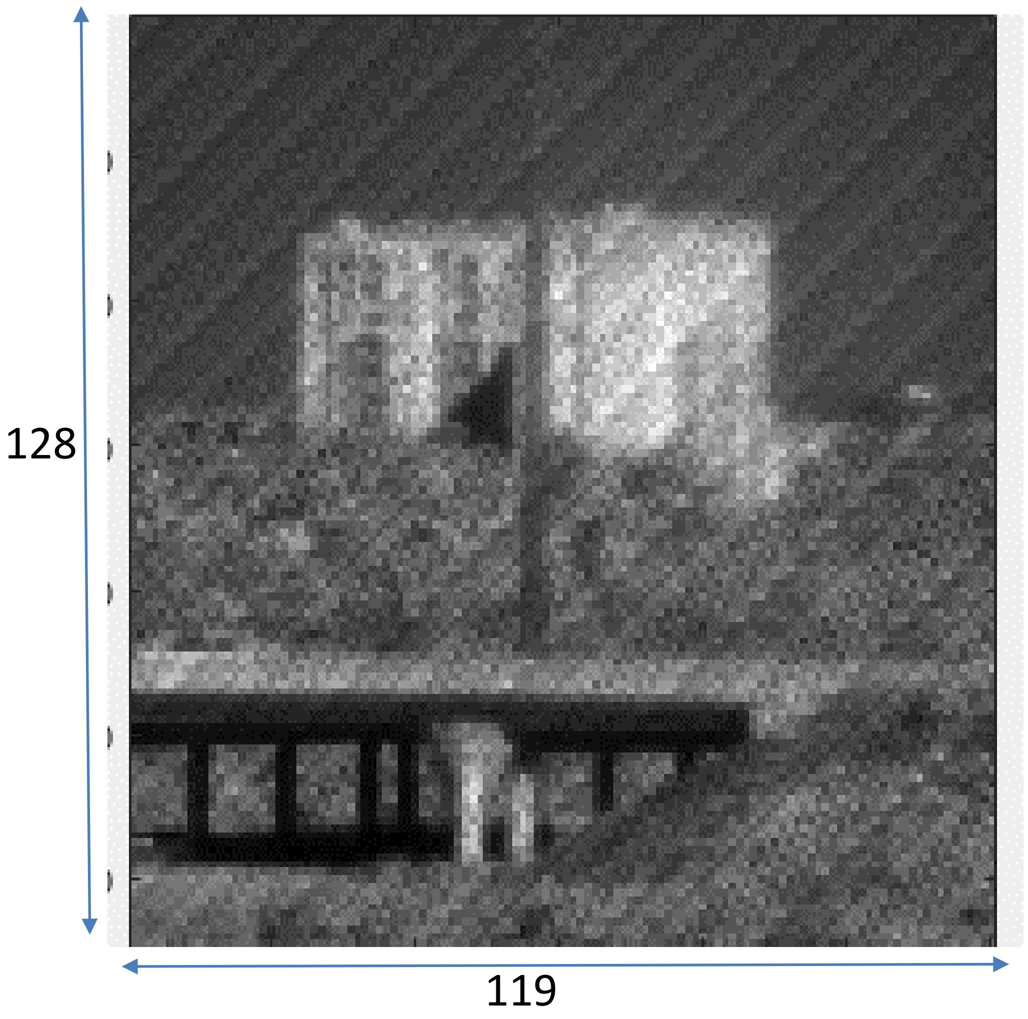
128 x 119
(17.6 micron pixel)
Low Resolution
image



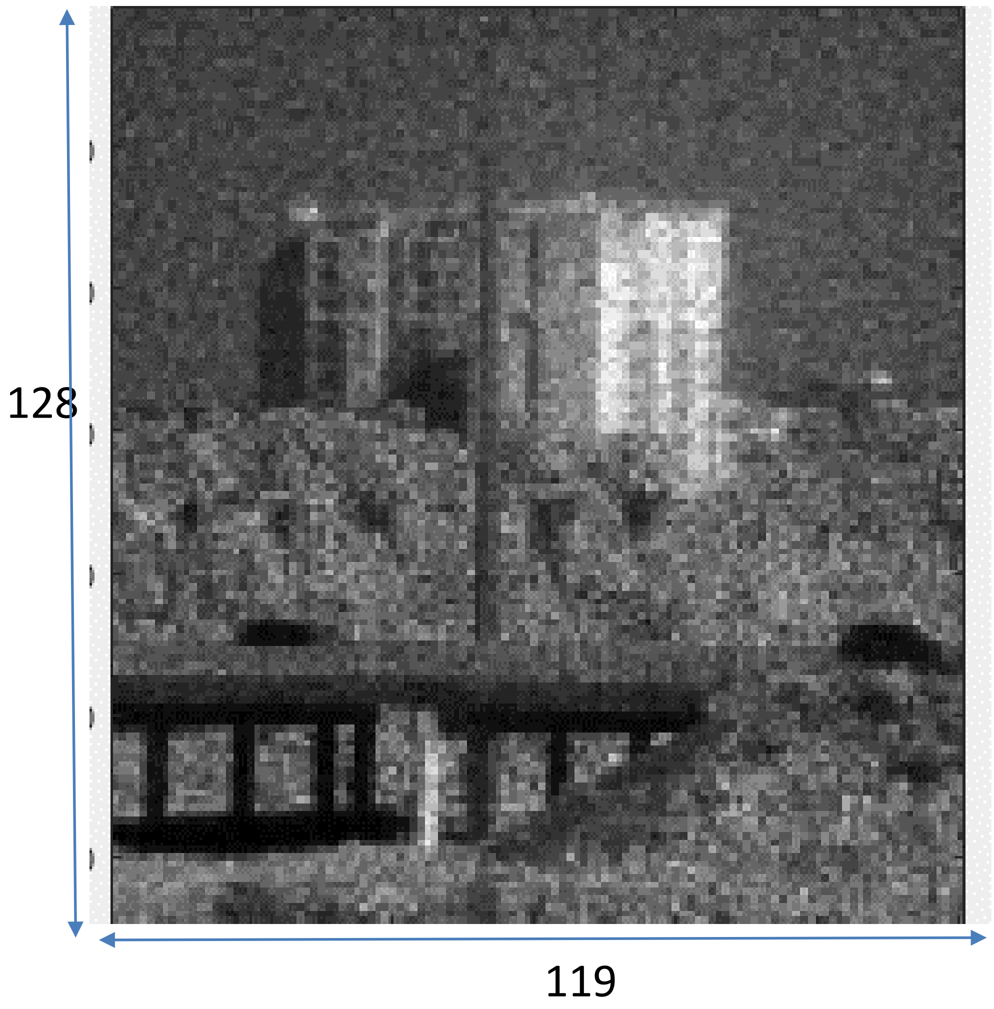
1024 x 952 (2.2
micron pixel)
High Resolution
image

- FPA data is digitally binned (in groups of 8x8 pixels) to obtain low resolution images

Video of low resolution data captured with 4X and 10X Masks



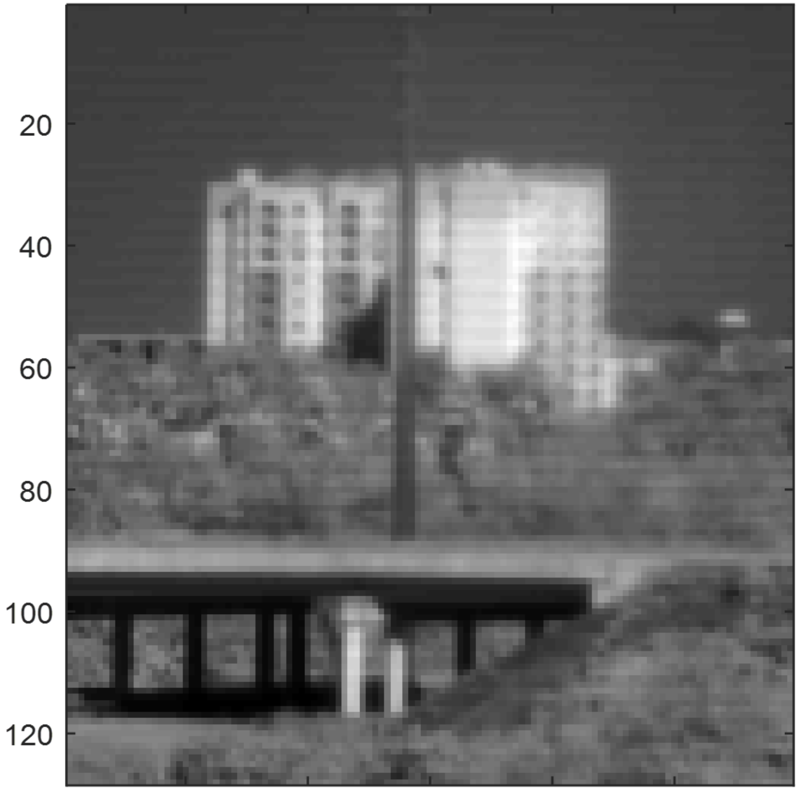
FPA data encoded with 1:4 mask



FPA data encoded with 1:10 mask

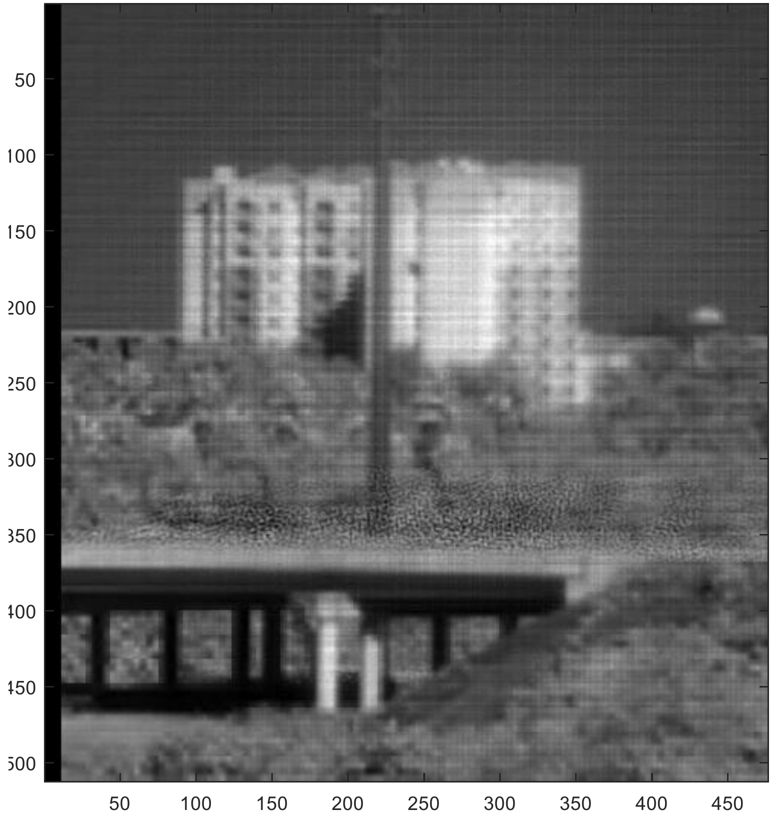
Comparison of Reconstruction Results (blockwise least squares)

128 x119



Average of data frames
Upsampled with bilinear interpolation

512 x476



4X Reconstruction using data encoded with 25 micron features (1:4 encoding)

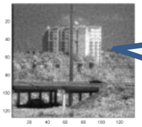
1024 x 952

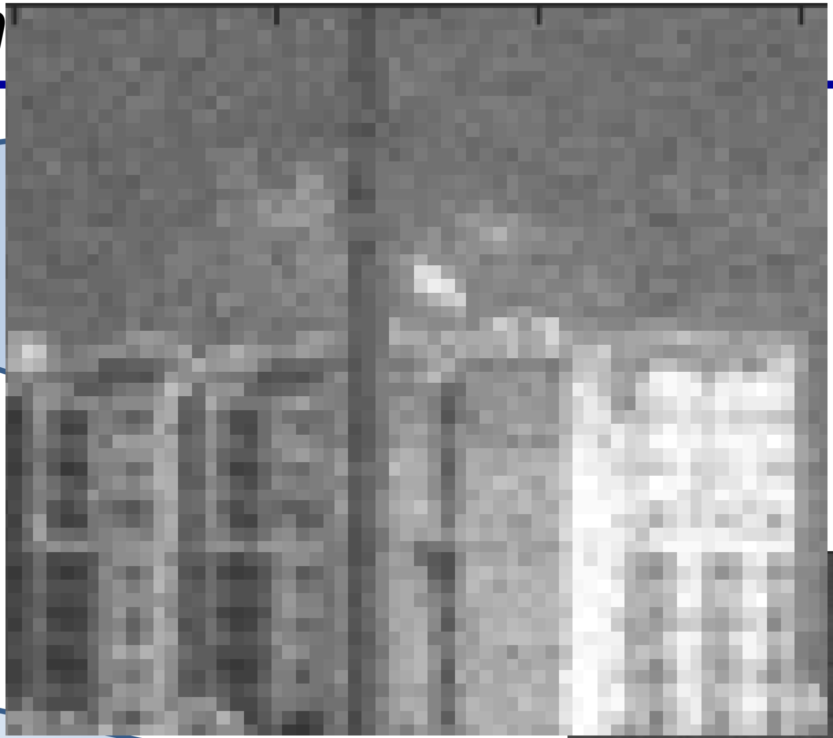
8X Reconstruction using data encoded with 10 micron features (1:10 encoding)

- The 8X has the best resolution
- The 4X reconstruction is better than the upsampled images, but not as good as the results obtained with 1:10 encoding

Details in 8X reconstruction

Low resolution
FPA frame
128 x 119
(after 8x8 binning)

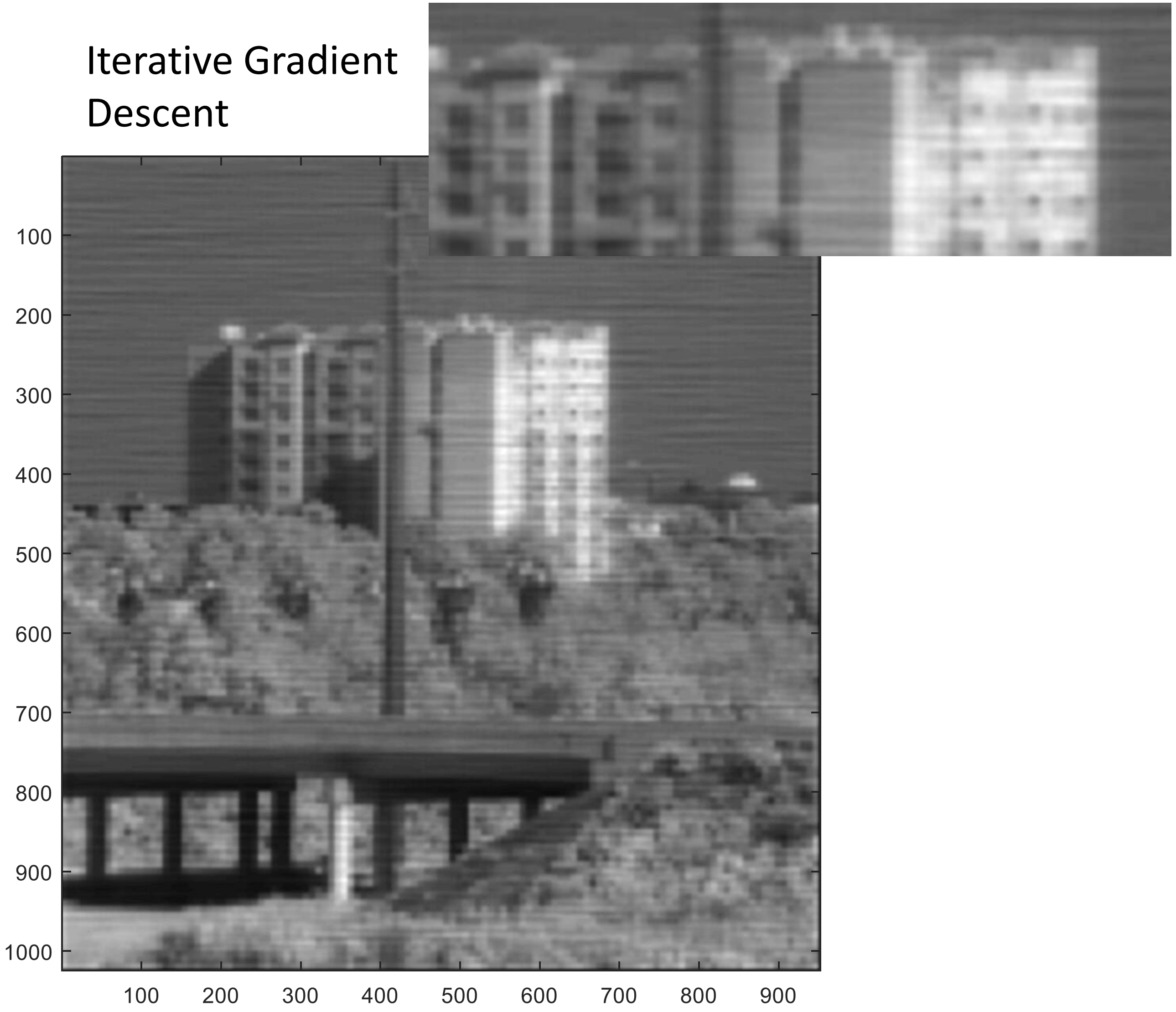




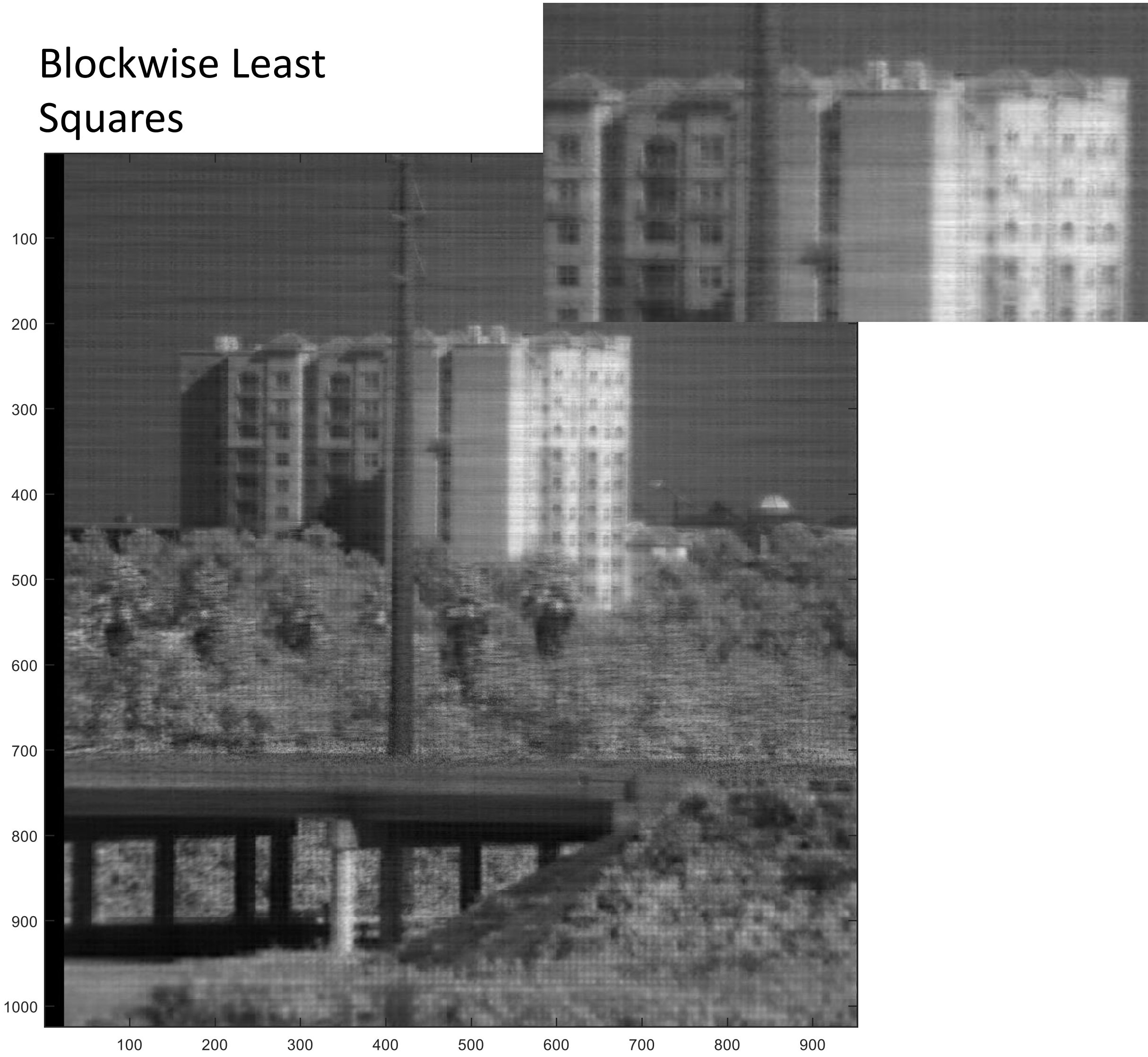
8X reconstruction
1024 x 952

Comparison of Gradient Descent and Blockwise LSQ

Iterative Gradient Descent

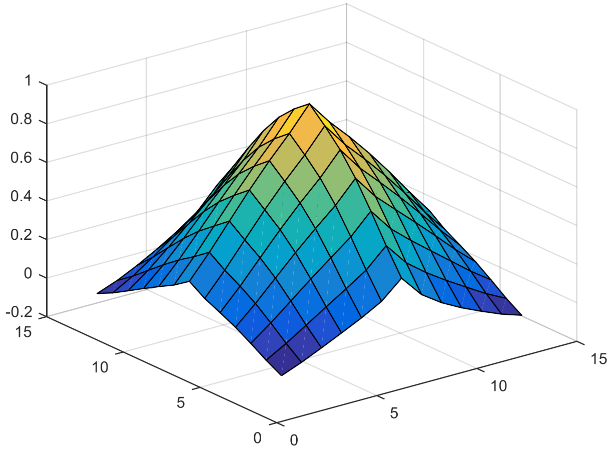


Blockwise Least Squares

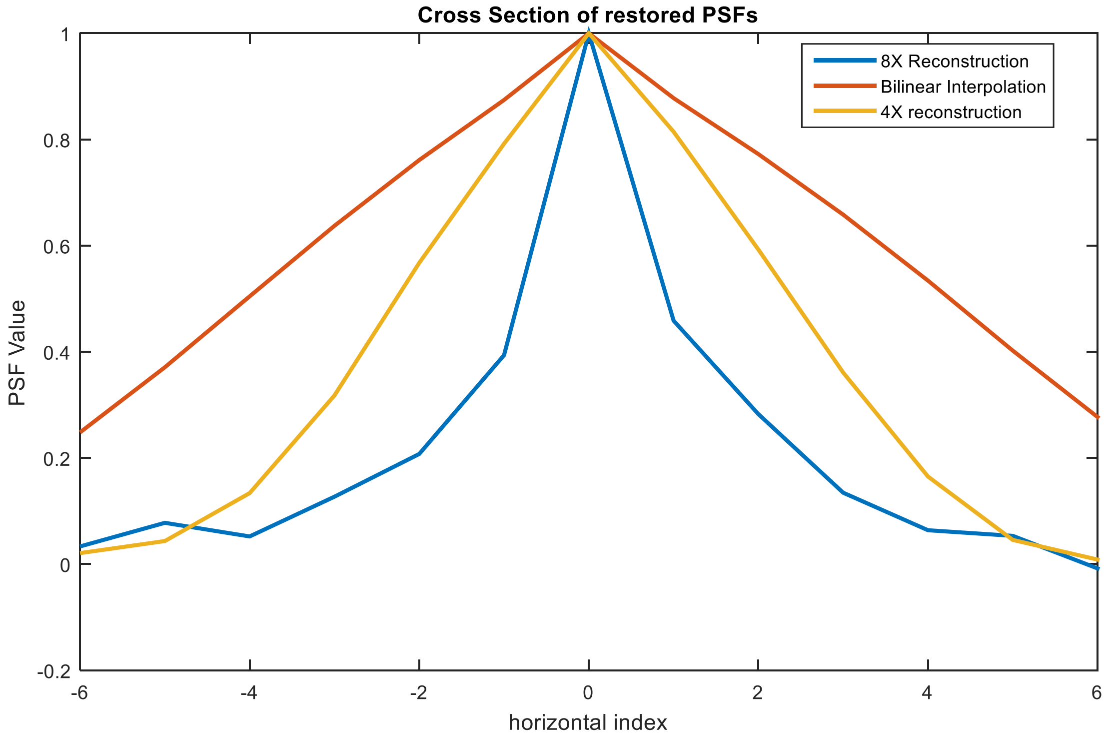


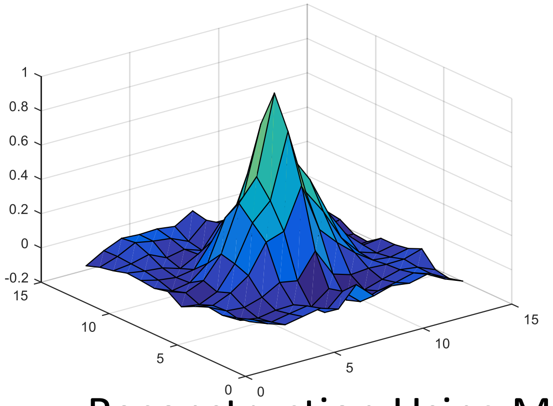
- The results obtained with the iterative least mean square (LMS) gradient descent algorithm (on the left) is somewhat more blurry than that obtained with the blockwise least squares algorithm (on the right).

Comparison of restored PSFs

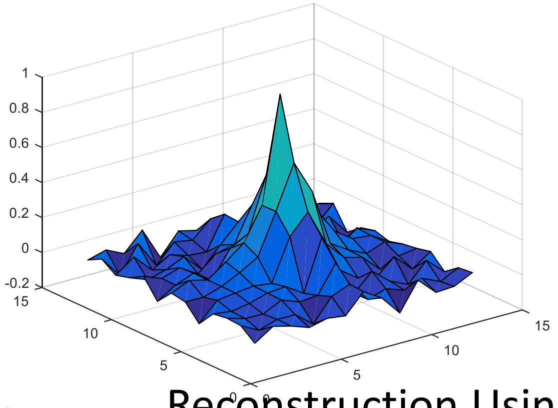


Upsample with
Bilinear interpolation





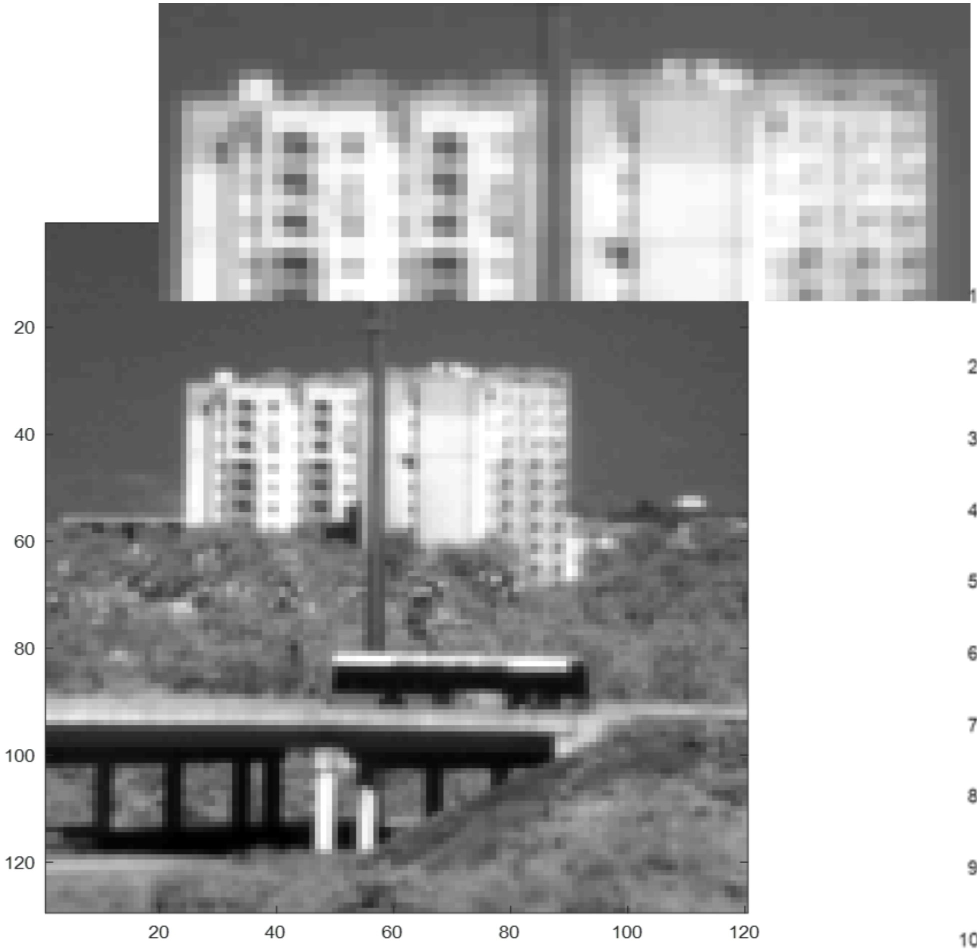
Reconstruction Using Mask
with 25 micron features

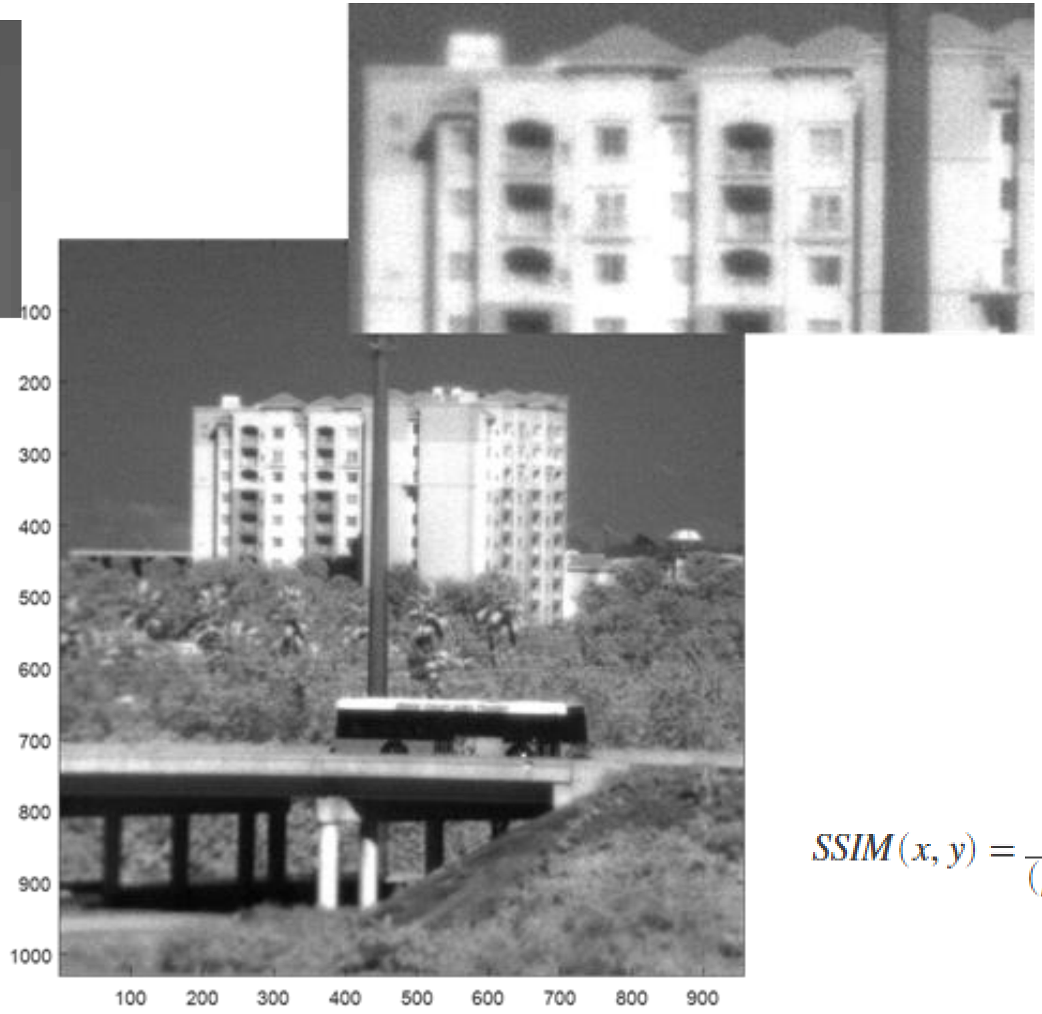


Reconstruction Using Mask
With 10 micron features

- The resolutions of the ideal and reconstructed images can be compared in terms of a “blur”
  - Narrower the blur, the better is the resolution of the reconstructed image.
- The 8X reconstruction has the narrowest blur. The 4X reconstruction comparatively broader (as expected), but still narrower than bilinear interpolation

Comparison of low and high resolution images using SSIM

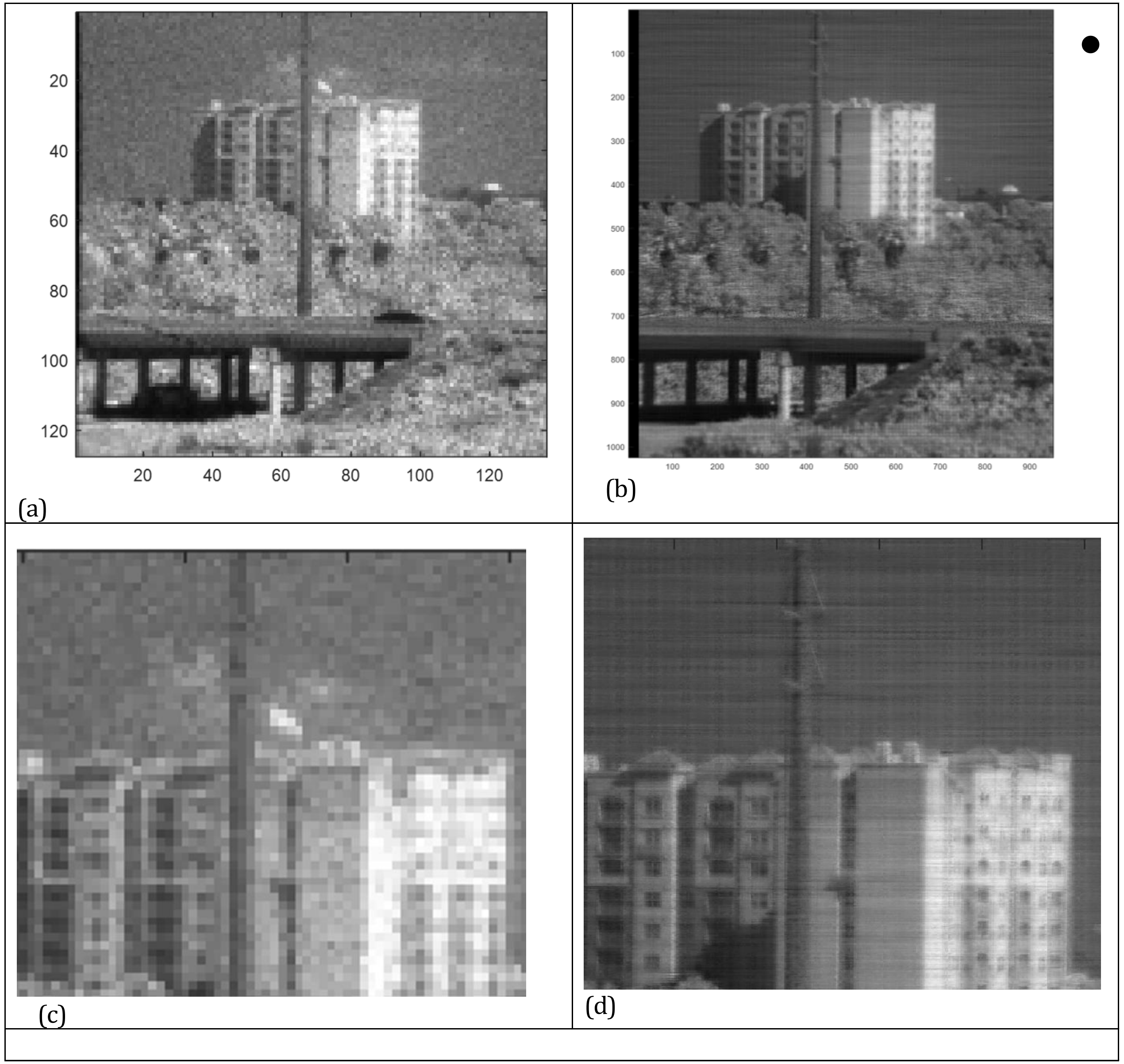




$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

- An outdoor scene (a) as captured at low resolution by the FPA with an SSIM measure of **0.34**, and (b) the ideal high resolution version showing the details to be reconstructed.

SSIM using Random Mask and blockwise Reconstruction

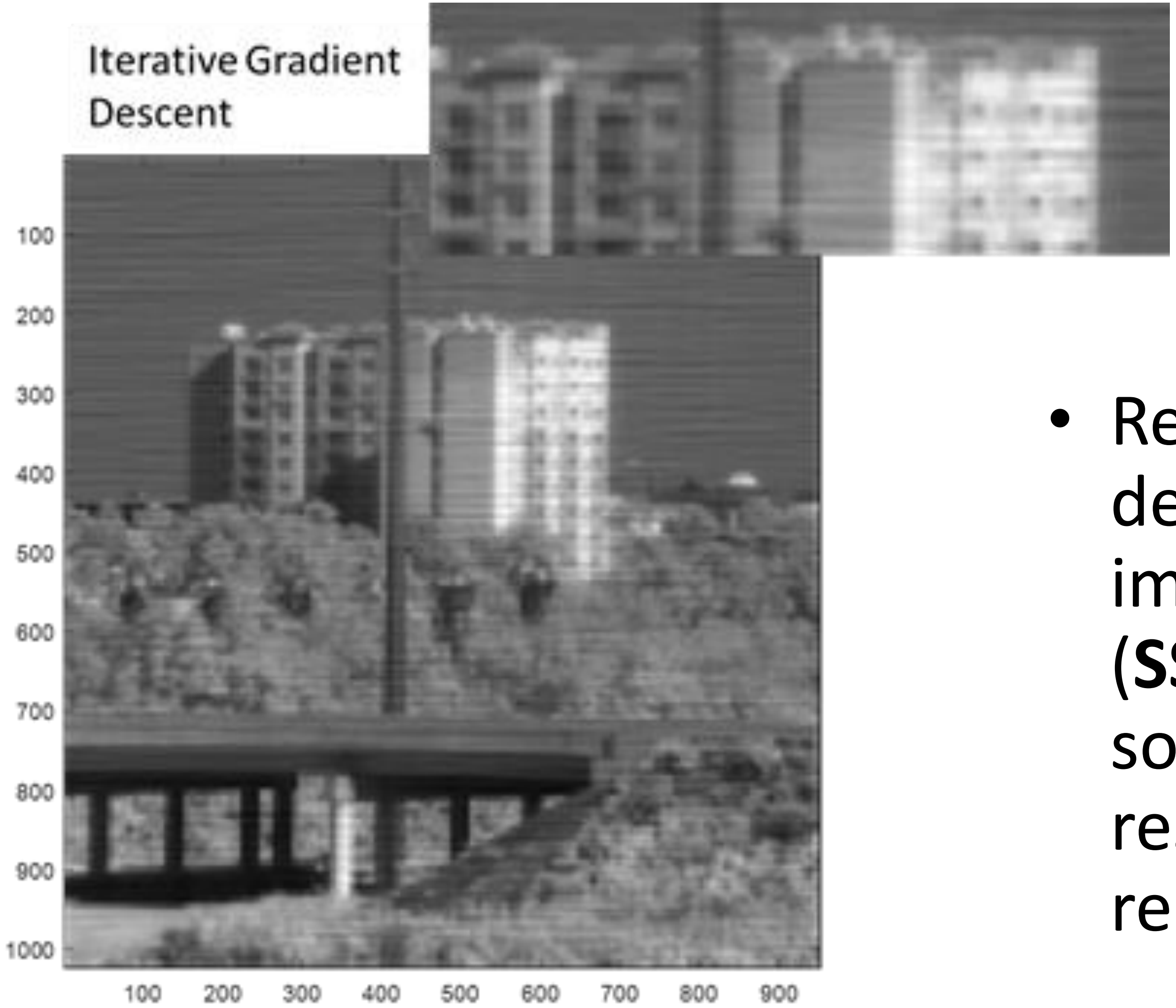


- The image in (a) is an example of data coded with the random mask. The result in (b) was obtained by tiling together 32 x 32 image blocks that were reconstructed using the corresponding 4x4 block of encoded data. The SSIM measure between this image and the ideal version **is 0.94**. Some details of the images in (a) and (b) are shown in (c) and (d) respectively.

Similarity Measure using Periodic Mask

- The results obtained with periodic mask has four-fold greater resolution than the original data (**SSIM=0.66**), but is comparatively blurry and noisy due to the poorly conditioned measurement matrix.

SSIM using Gradient Descent with Random Mask



- Results obtained with gradient descent algorithm exhibit improved resolution (**SSIM=0.86**), but details are somewhat blurry compared to results obtained with blockwise reconstruction.

Summary

- We have experimentally verified that high resolution images can be obtained using considerably smaller FPAs
  - This is a trade off between space bandwidth and time
- Coding with moving mask allows improvement in resolution by 8X in each dimension (1:64 increase in pixels)
  - This implies that a 1K x 1K FPA can be used to create 8K x 8K images
  - We showed that there is an optimum number of shifts between measurements
  - Results illustrate the importance of incorporating photon constraints
  - Two different reconstruction algorithms were used (iterative gradient descent and blockwise reconstruction)
- Comparison of recovered MTFs show that 10micron mask doubles the resolution obtained using 25 micron mask
- Comparison of SSIM values show that blockwise reconstruction using least squares is better than iterative gradient descent