Airborne Synthetic Aperture Radar Image Super Resolution technique for better visualization for remote sensing applications

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Walk throu....... ....

1. Synthetic? Aperture? Radar! (Scenario)
2. Reason for Super resolution (Problem)
3. Super Resolution Technique (Proposed algorithm)
4. Simulation Results (Proofs)

Synthetic? Aperture? Radar!

Radarrr →

Radio Detection and Ranging

WW II, England. Military use

measure backscattered amplitude and distance to target

High power, sharp pulse -> low power, FM-CW chirp signal

- Navigation radar, Weather radar
- Ground penetrating Radar, Imaging radar

Imaging Radar →

Different Eyes microwave, UHF, VHF

surface roughness and dielectric constant

Microwave Ranging

- All-weather
- Cloud-free
- Side-looking

Active System

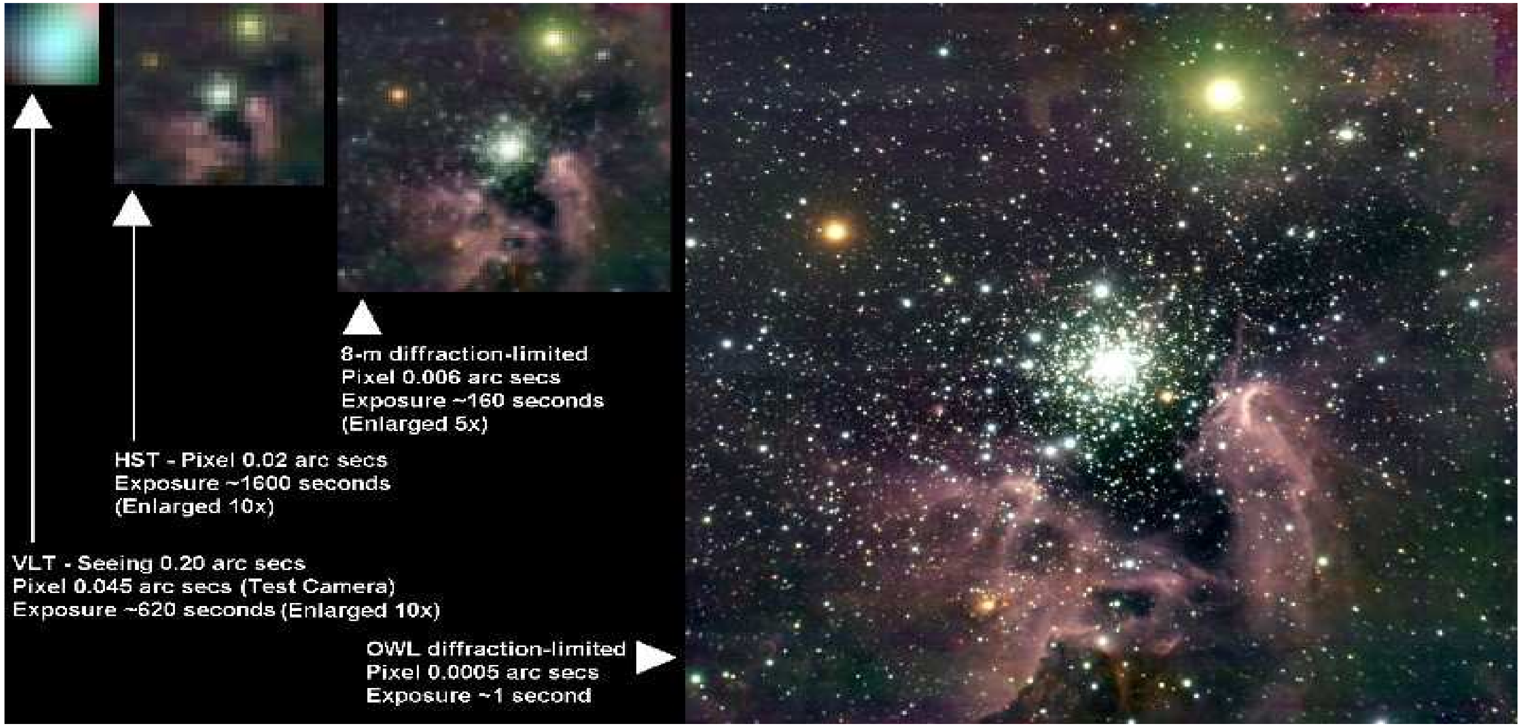
- Day and night imaging
- independent of solar illumination

Synthetic? Aperture? Radar!

Aperture

Optics : Diameter of the lens or mirror. The larger the aperture, the more light a telescope collects. Greater detail and image clarity will be apparent as aperture increases.

- 2.4m Hubble Space Telescope
- 10m Keck, Hawaii
- 16.4m VLT (Very Large Telescope), Chile
- 50m Euro50
- 100m OWL (OverWhelmingly Large T.)



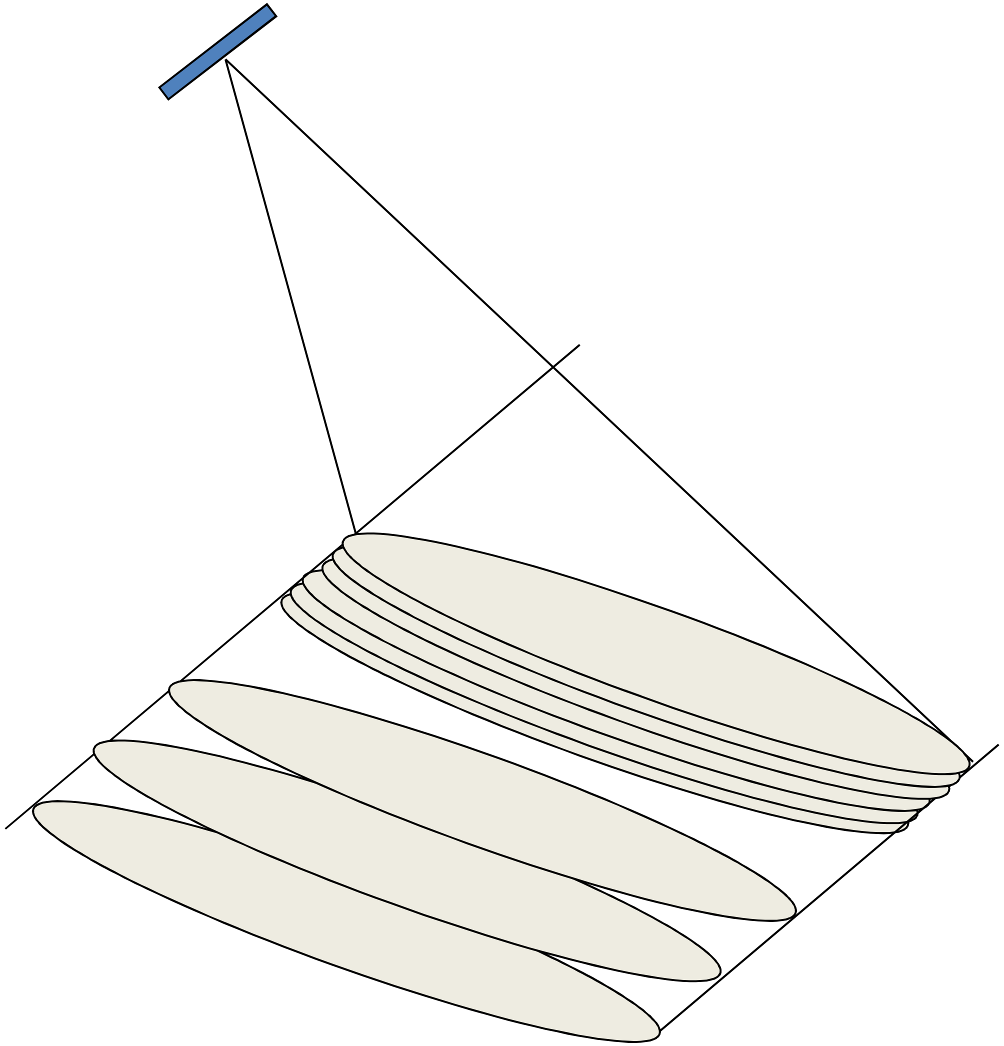
Courtesy SAR ppt download from web

Real Aperture vs. Synthetic Aperture

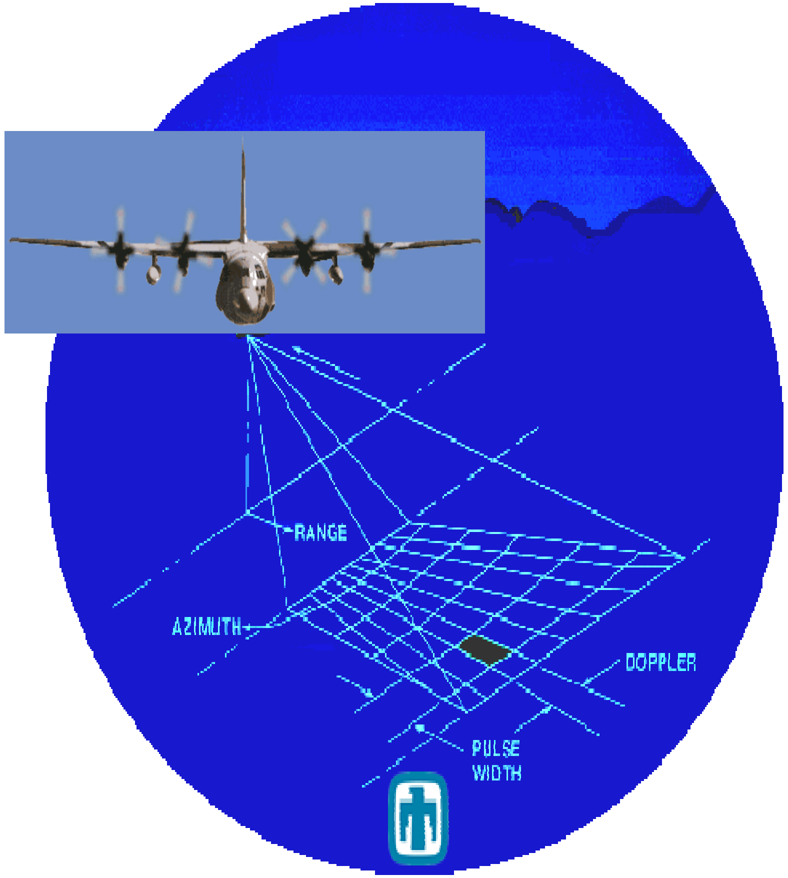
- Real Aperture :
  resolution ~ $R\lambda/L$

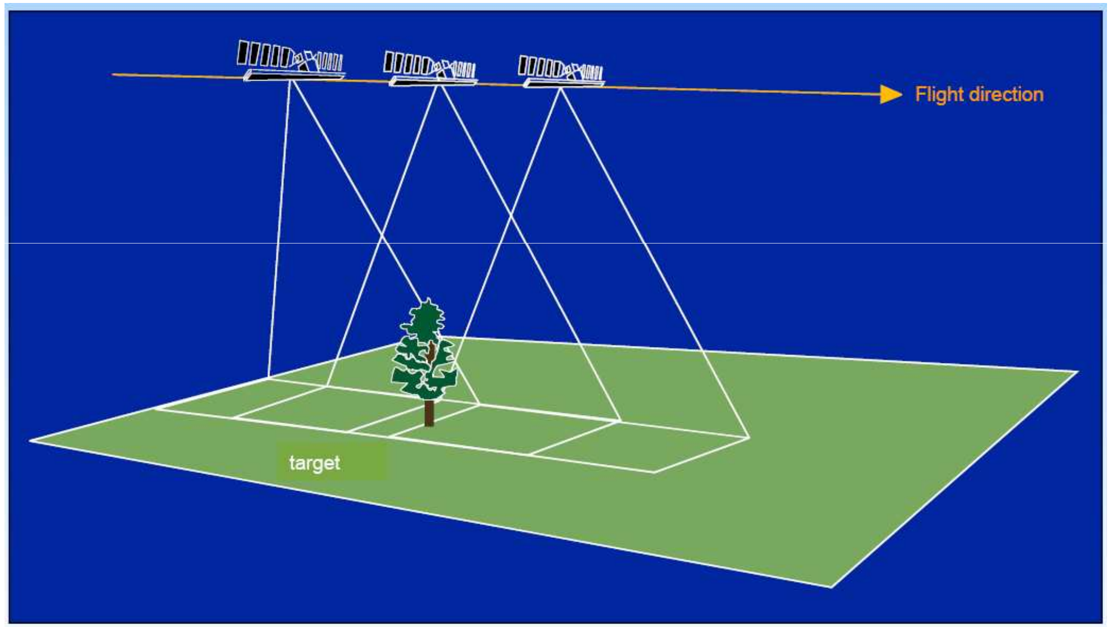
- Synthetic Aperture:
  resolution ~ $L/2$

  Irrespective of R
  Smaller, better?!
  - Carl Wiley (1951)



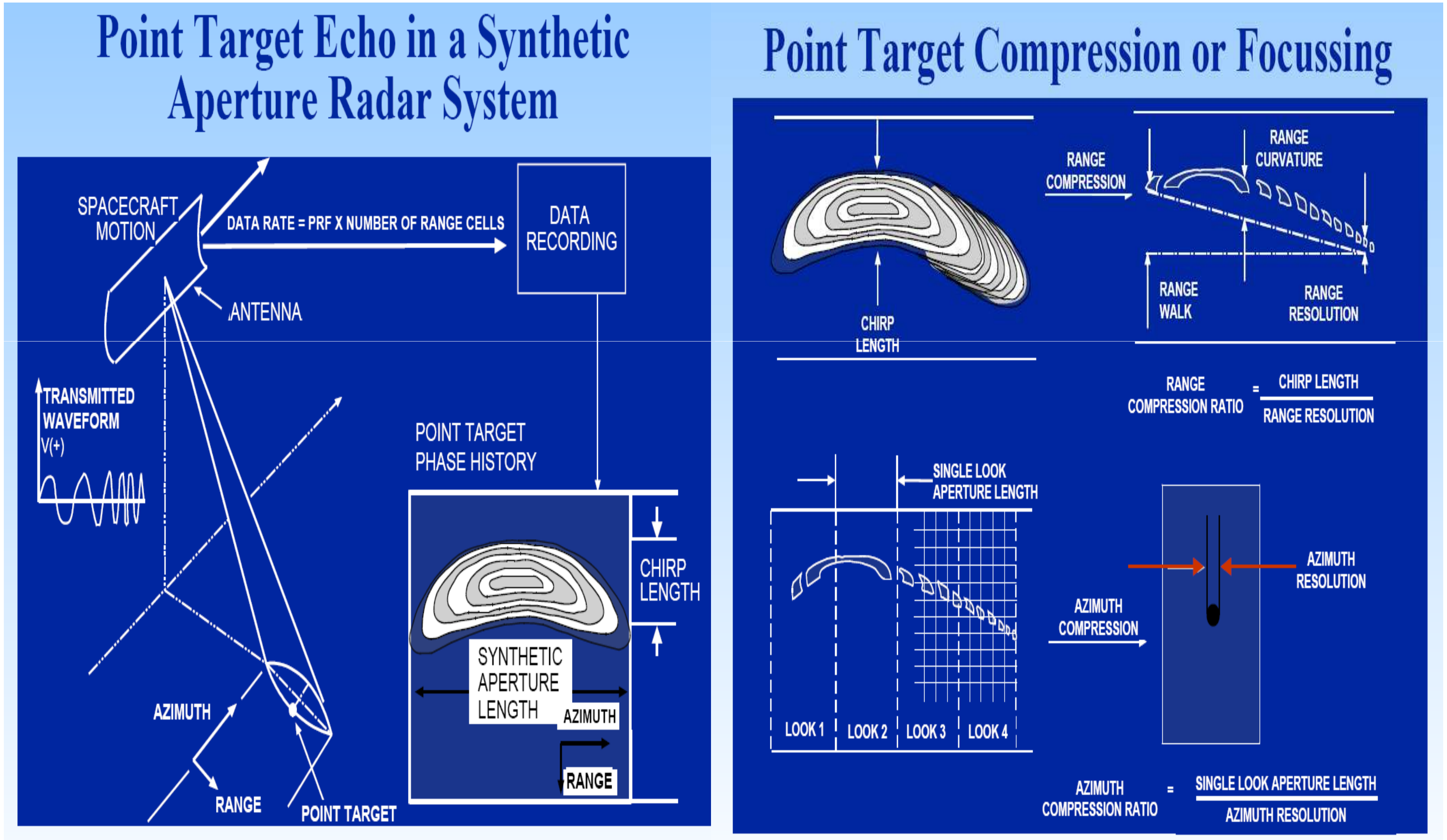
Synthetic Aperture Radar Imaging Principles





Courtesy **SAR ppt download from web**

Synthetic Aperture Imaging Principles



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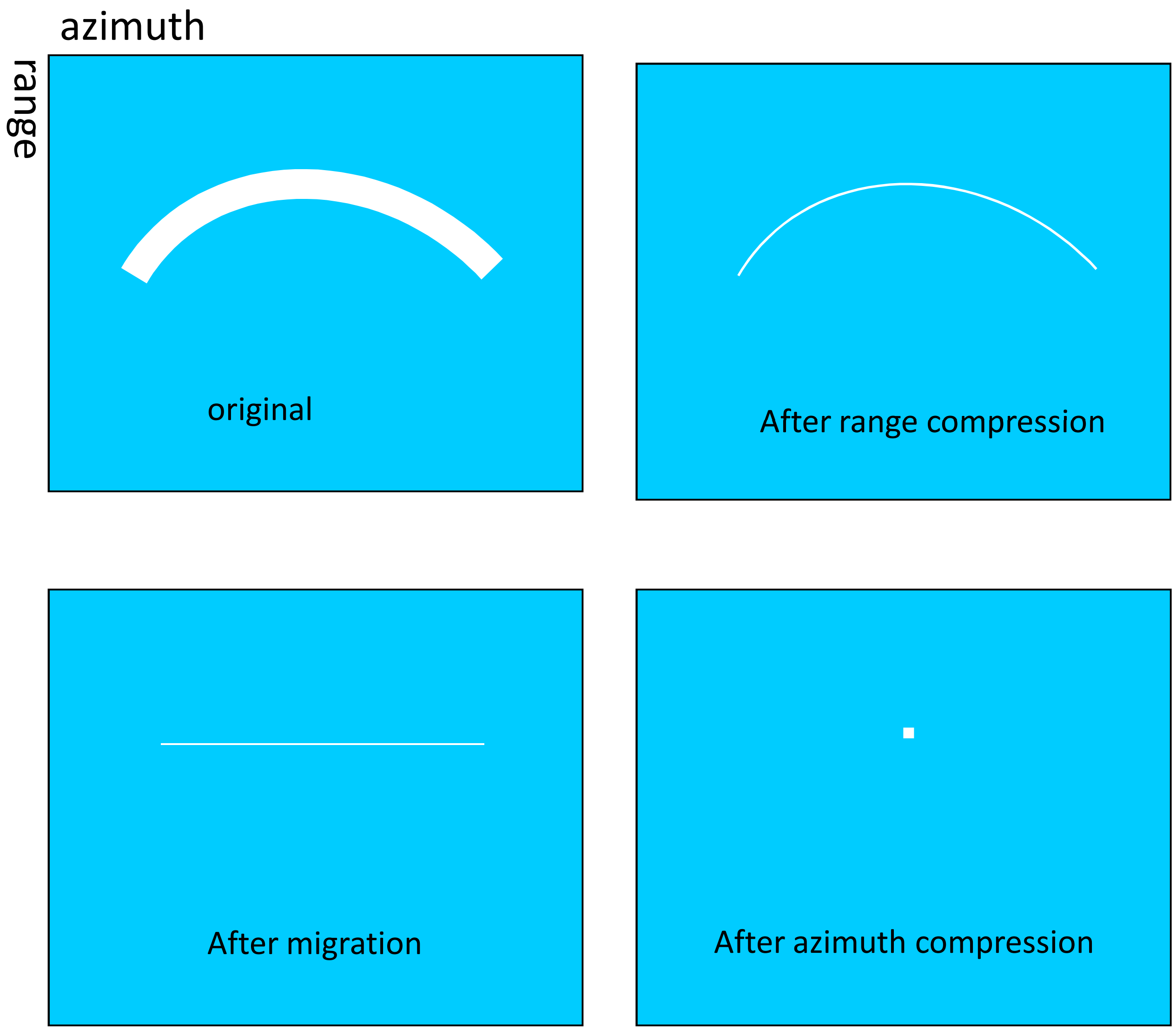
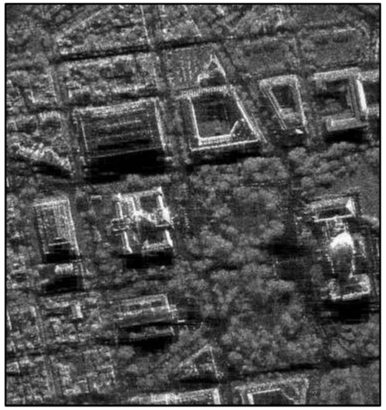
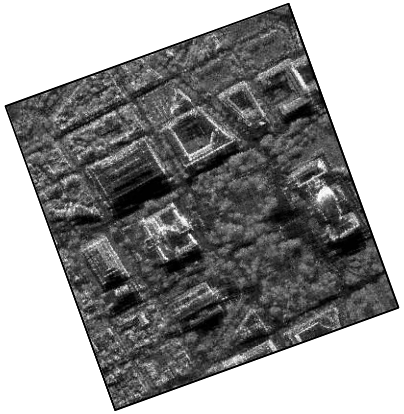
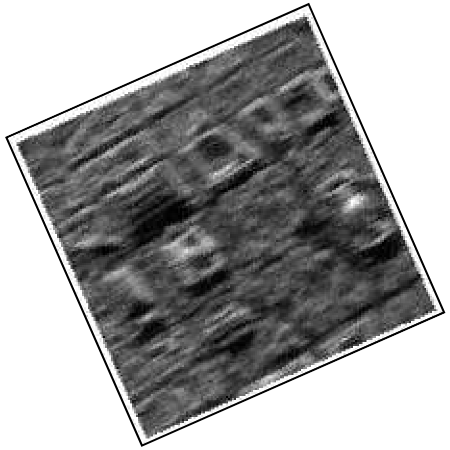
Synthetic Aperture Radar Imaging Principles



Low Resolution Image formation







Scene

Geometric transformation + Sampling

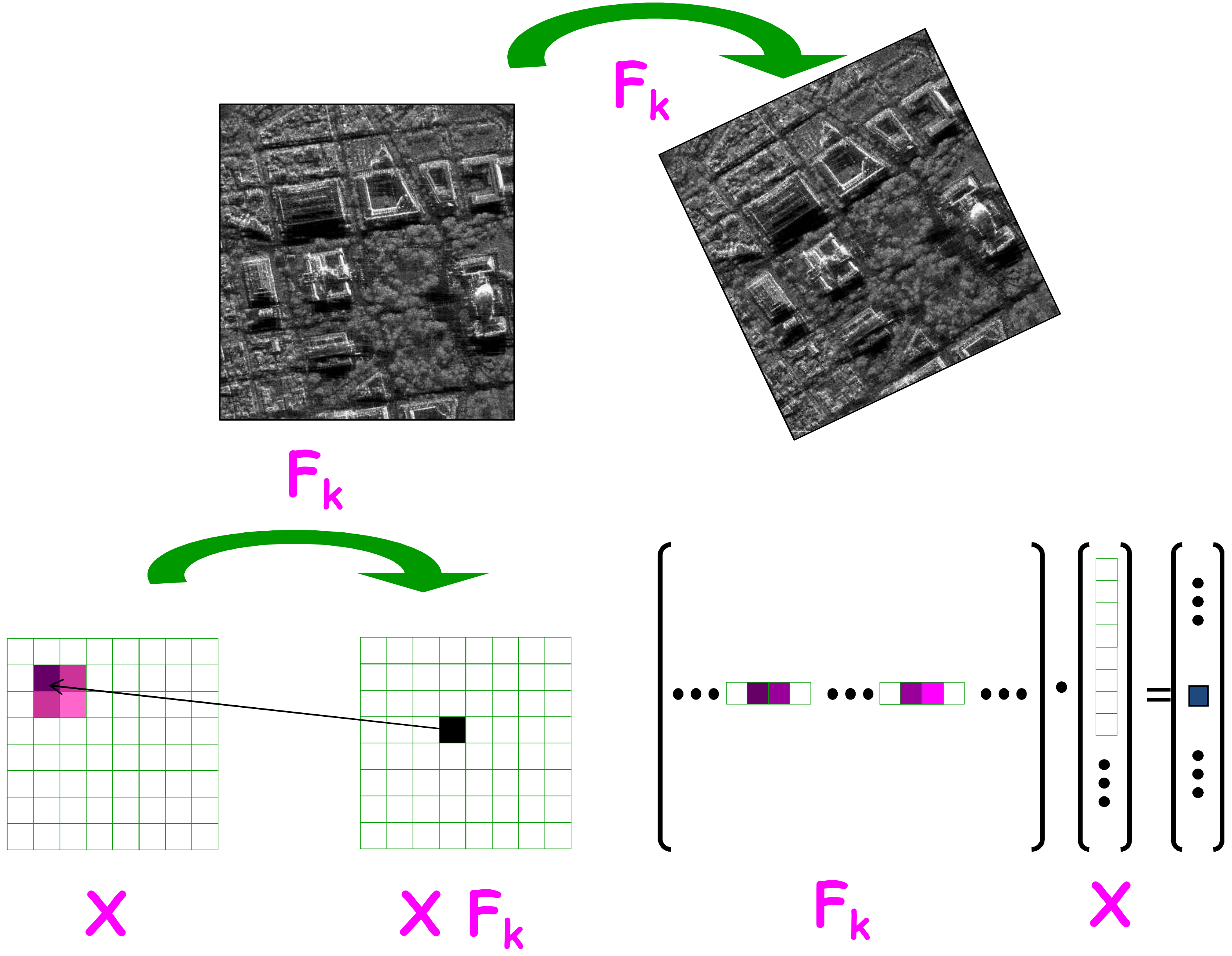
Blur + Noise

HR **F_k** **D_k** **H_k** **LR**

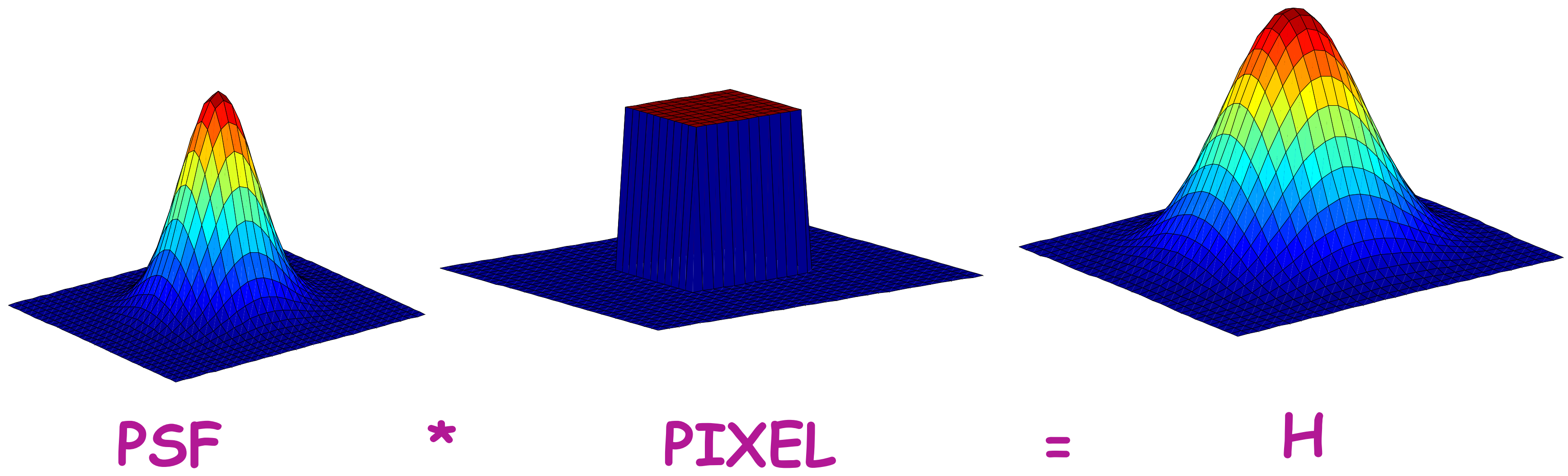
Can we write these steps as linear operators?

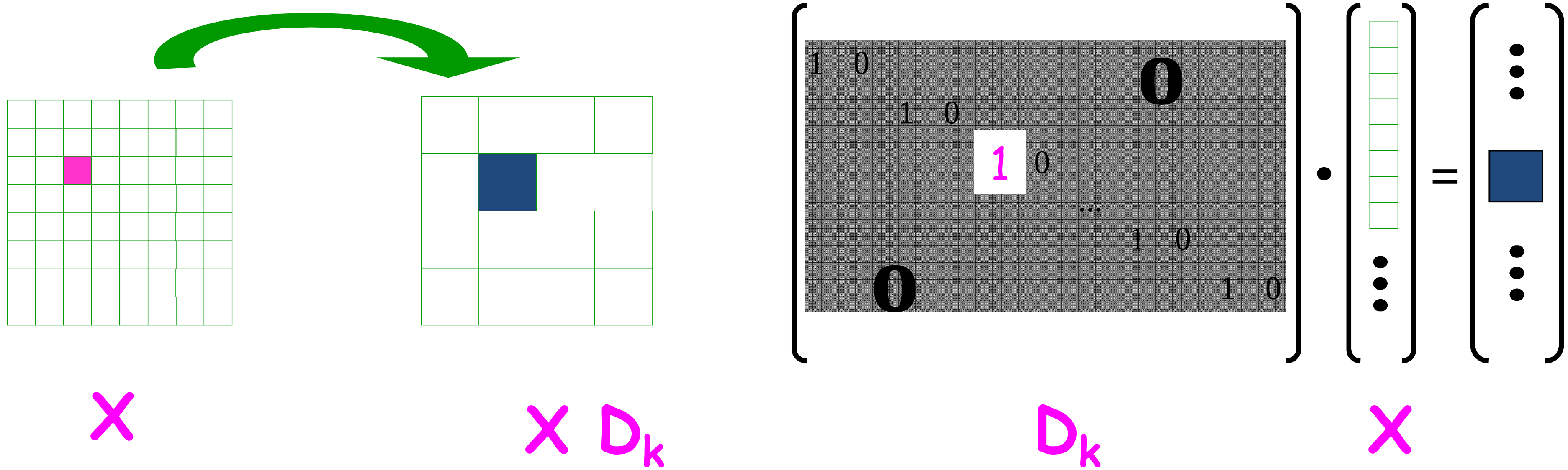
$$LR = D_k H_k F_k \cdot HR$$

Geometric transformation

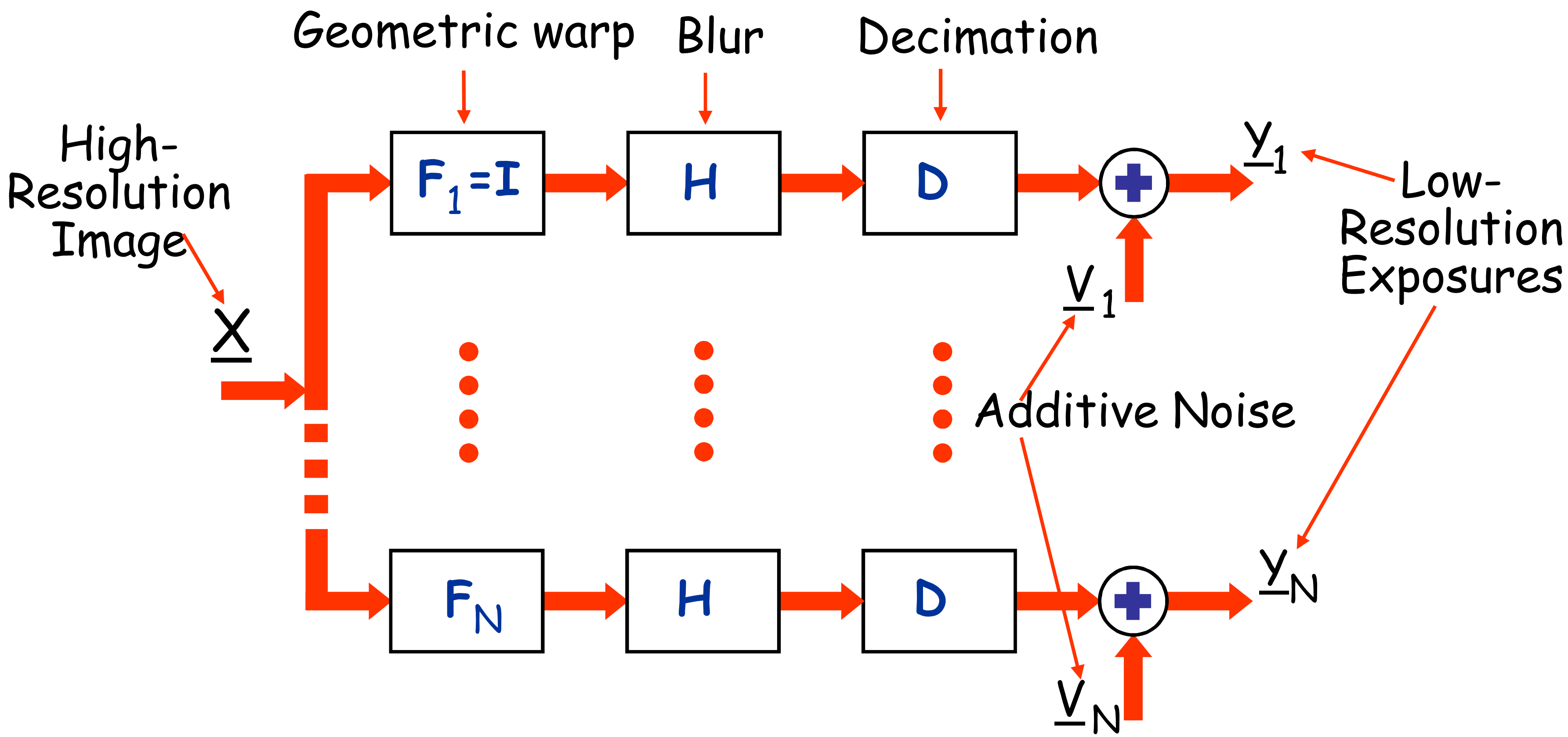


Noise & Sampling





Model of low resolution image



$$\left\{ \underline{Y}_k = \mathbf{DHF}_k \underline{X} + \underline{V}_k, \quad \underline{V}_k \sim \mathbf{N}\left\{0, \sigma_n^2\right\} \right\}_{k=1}^{N}$$

Model of Low Resolution Image

$$\underline{Y}_k = \mathbf{DHF}_k \underline{X} + \underline{V}_k, \quad \underline{V}_k \sim \mathbf{N}\left\{0, \sigma_n^2\right\}$$

- Given

  $\underline{Y}_k$ – The measured images (noisy, blurry, down-sampled ..)

  H – The blur can be extracted from the camera characteristics

  D – The decimation is dictated by the required resolution ratio

  $\mathbf{F}_k$ – The warp can be estimated using motion estimation

  $\boldsymbol{\sigma_n}$ – The noise can be extracted from the camera / image

- Recover

  $\underline{X}$ – HR image

Solution for Super Resolution

- Maximum Likelihood (ML):

$$\underline{X} = \arg\min_{\underline{X}} \sum_{k=1}^{N} \left\| \mathbf{DHF}_k \underline{X} - \underline{Y}_k \right\|^2$$

Often ill posed problem!

- Maximum Aposteriori Probability (MAP)

$$\underline{X} = \arg\min_{\underline{X}} \sum_{k=1}^{N} \left\| \mathbf{DHF}_k \underline{X} - \underline{Y}_k \right\|^2 + \lambda A\{\underline{X}\}$$

Smoothness constraint regularization

Solution for Super Resolution Image

- Denoising (single frame)

$$\underline{Y} = \underline{X} + \underline{V}, \quad \underline{V} \sim \mathbf{N}\left\{0, \sigma_n^2\right\}$$

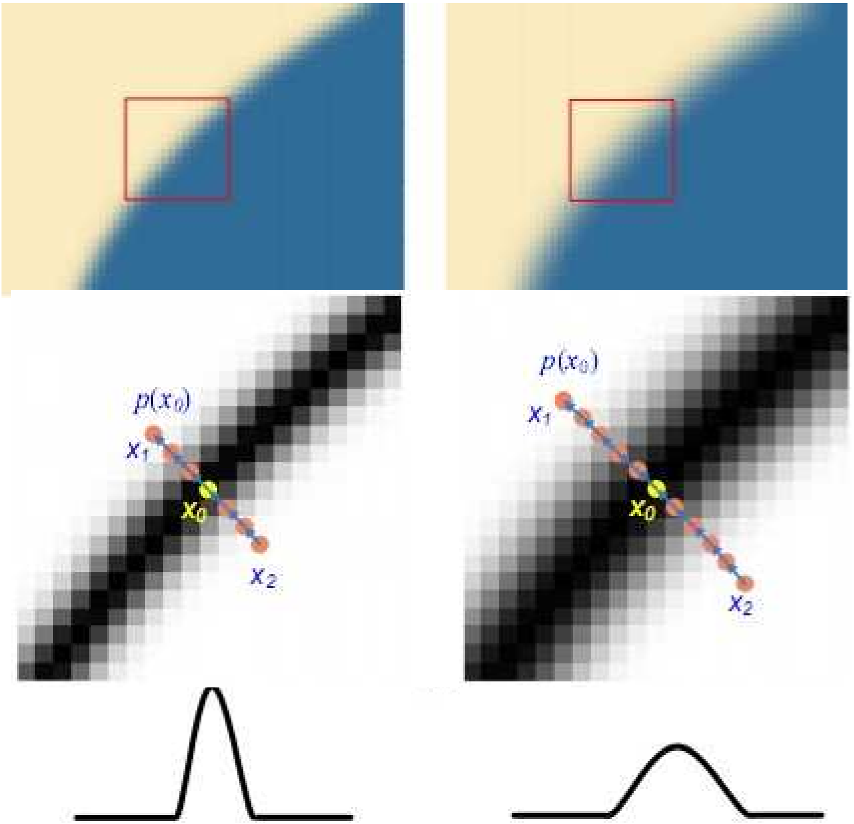
- Deblurring

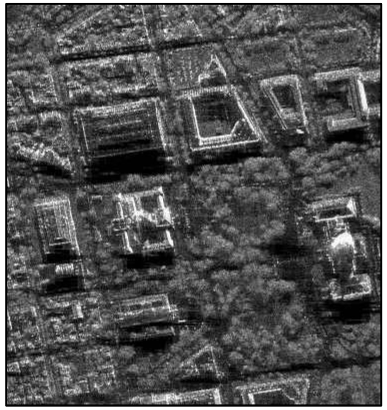
$$\underline{Y} = \mathbf{H}\underline{X} + \underline{V}, \quad \underline{V} \sim \mathbf{N}\left\{0, \sigma_n^2\right\}$$

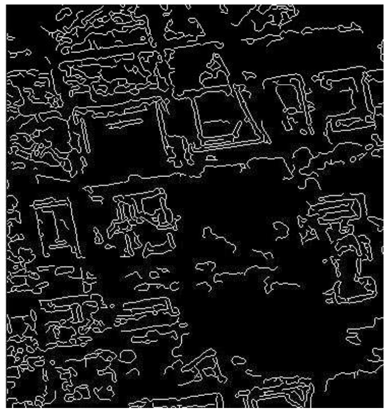
- Interpolation – "single-image super-resolution"

$$\underline{Y} = \mathbf{DH}\underline{X} + \underline{V}, \quad \underline{V} \sim \mathbf{N}\left\{0, \sigma_n^2\right\}$$

Solution for Super Resolution Image







Left is the natural image and its gradient field. Denote the Image gradient as $\nabla I = m \cdot \vec{N}$, where m is the gradient magnitude and $\vec{N}$ is the gradient direction. In the gradient field, we denote the zero crossing pixel which is the local maximum on its gradient direction as edge pixel.

Edge directed SR via gradient profile prior(GPP)

It has been shown that the 1D profile of edge gradients in natural images follows a distribution that is independent of resolution. This so-called gradient profile prior (GPP) provides an effective constraint for upsampling LR images.

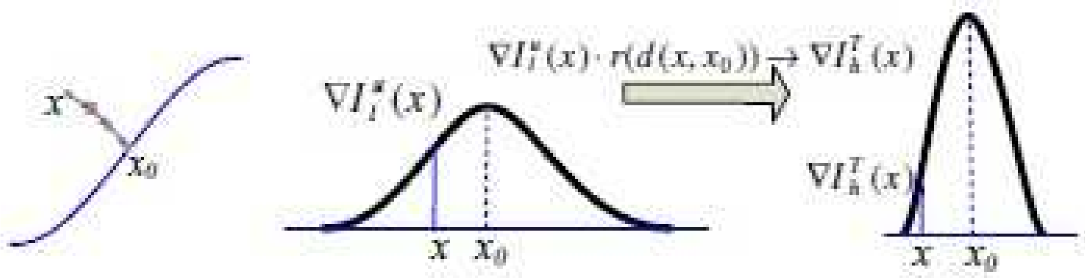
The gradient profile distribution is modeled by a generalized Gaussian distribution (GGD) as follows:

$$g(x;\sigma,\lambda) = \frac{\lambda\alpha(\lambda)}{2\sigma\Gamma(\frac{1}{\lambda})}\exp(-(\alpha(\lambda)|\frac{x}{\sigma}|)^{\lambda})$$

where

$$\alpha(\lambda) = \sqrt{\Gamma(\frac{3}{\lambda})/\Gamma(\frac{1}{\lambda})}$$

Edge directed SR via gradient profile prior(GPP)



To estimate a sharp SR gradient field based on the GPP, we can transform the gradient field of the bicubic upsampled LR image by multiplying the ratio between the gradient profiles of natural images and the gradient profiles of bicubic upsampled LR images as follows:

$$\nabla_g I_H = \frac{g(d; \sigma_h, \lambda_h)}{g(d; \sigma_l, \lambda_l)} \nabla I_L$$

After gradient transformation, a sharper and thinner gradient field is obtained as shown in the processing pipeline. This procedure serves as the starting point of our detail synthesis described in the following section.

Synthesis of details via example- extracting structural and detail patches

Given the edge-directed SR gradient field $\nabla_g I_H$ obtained using GPP, and an example image I_E , we now compute the full gradient field prior $\nabla_p I_H$ that includes synthesis of details. The input example image I_E represents the look-and feel for the desired HR image and is assumed to be at the resolution of the HR image. From I_E , example patches are extracted for detail synthesis.

In order to better represent edge structure, we extract structure patches from the example image I_E in the following manner. We first downsample I_E to match the scale of the LR image, and then upsample its gradient field using GPP to obtain $\nabla_g I_E$, which represents the salient edge structure in I_E . We now form a set of exemplar patch pairs $\{\nabla E_i, \nabla_g E_i\}$, where *texture patches*, ∇E_i , come directly from I_E and the corresponding *structural patches*, $\nabla_g E_i$, come from the $\nabla_g I_E$. Structural patches $\nabla_g E_i$ are different from ∇E_i , especially as magnification increases.

Edge directed SR Frame work

Within the reconstruction framework, the goal is to estimate a new HR image, I_H , given the low resolution input image I_L and a target gradient field $\nabla_p I_H$. This can be formulated as a Maximum Likelihood (ML) problem as follows:

$$
\begin{aligned}
I_H^* &= \arg\max_{I_H} P(I_H | I_L, \nabla_p I_H) \\
&= \arg\min_{I_H} L(I_L | I_H) + L(\nabla_p I_H | \nabla I_H) \\
&= \arg\min_{I_H} ||I_L - d(I_H \otimes h)||^2 + \beta ||\nabla_p I_H - \nabla I_H||^2
\end{aligned}
$$

Assuming that these data-costs follow a Gaussian distribution, this objective can be cast as a least squares minimization problem with an optimal solution I_H^* obtained by gradient descent with the following iterative update rule:

$$I_H^{t+1} = I_H^t + \tau(I_L - u(d(I_H^t \otimes h)) \otimes p + \beta(\nabla_p^2 I_H - \nabla^2 I_H))$$

Simulation Results (Proofs)

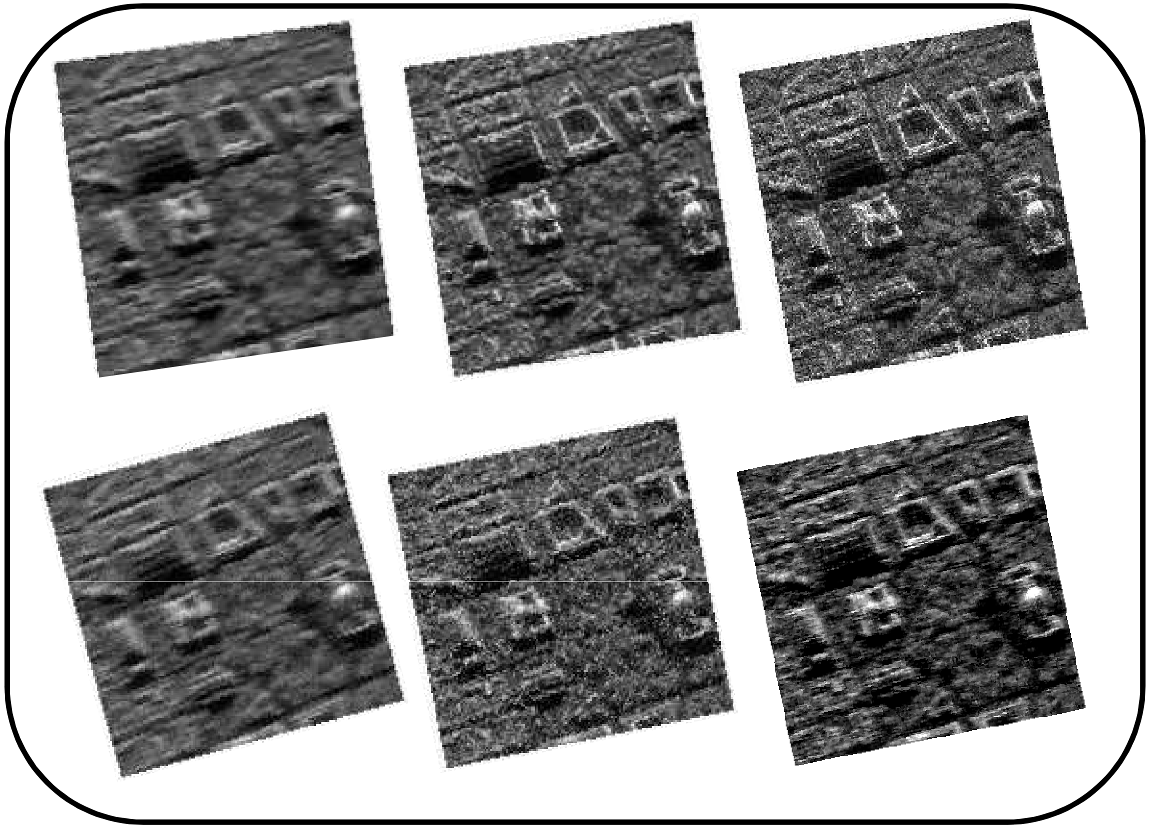
Matlab tool version 7.6.0 is used for the simulation of the proposed algorithm.

- Three images from the SAR image database are chosen to validate our proposed algorithm here.
- The noisy + blured image is also simulated with the specified noise variance.
- The images are tested with noise.

Performance Measures

- Peak Signal to noise Ratio,
- Mean Square Error,
- Absolute Difference,
- Normalized Cross Correlation,
- Structural Content

Simulation Results (Proofs)

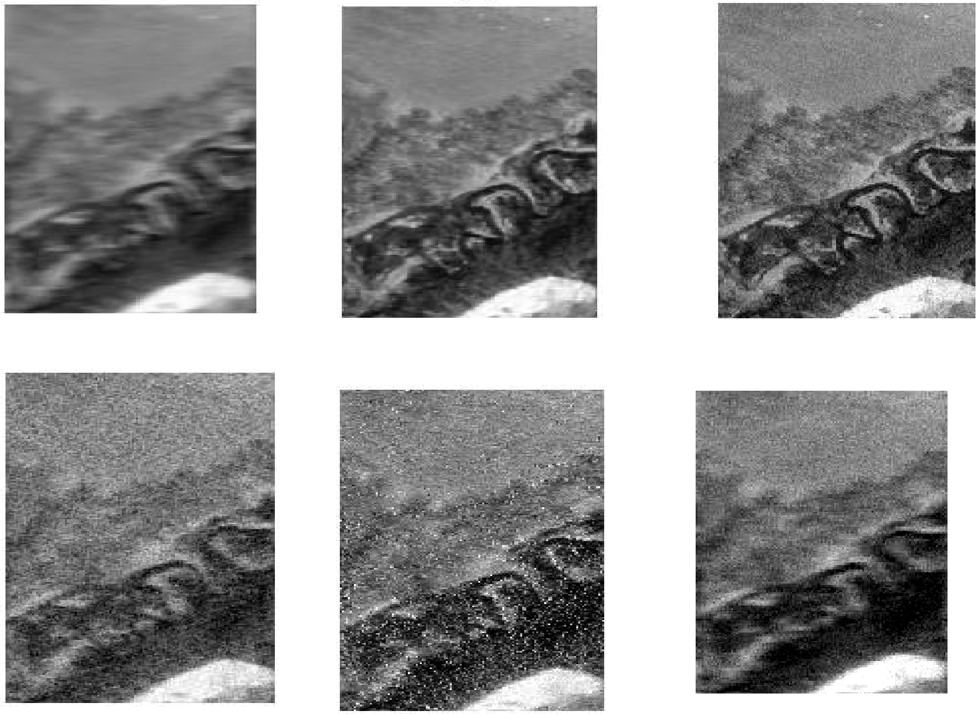


Test Results on SAR Image 3 . (a) Blurred image (b) Wiener filtered image (c) proposed algorithm (d) Blur+ noisy image (e) Wiener filtered image (f) proposed algorithm

Super resolution Efficiency measurement for SAR Image 1

Var=0.1	AD	NK	SC	MD	NAE
Proposed	12.828	0.88442	1.25357	112	0.14019
Wiener	0.125	0.9800	1.185	198	0.15639

Simulation Results (Proofs)

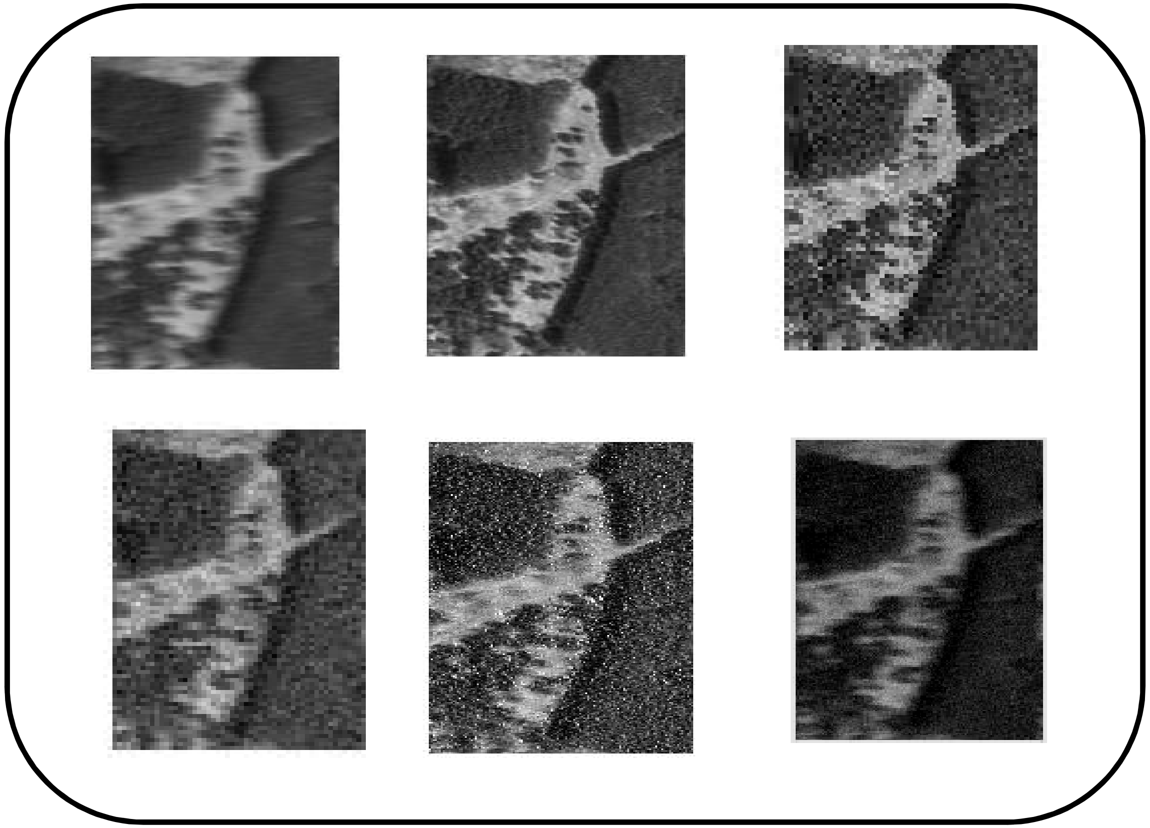


Test Results on SAR Image 3 . (a) Blurred image (b) Wiener filtered image (c) proposed algorithm (d) Blur+ noisy image (e) Wiener filtered image (f) proposed algorithm

Super resolution Efficiency measurement for SAR Image 2

Var=0.1	AD	NK	SC	MD	NAE
Proposed	11.828	0.988442	1.3457	112	0.14019
Wiener	0.125	0.9800	1.185	198	0.15639

Simulation Results (Proof)



Test Results on SAR Image 3 . (a) Blurred image (b) Wiener filtered image (c) proposed algorithm (d) Blur+ noisy image (e) Wiener filtered image (f) proposed algorithm

Super resolution Efficiency measurement for SAR Image 3

Var=0.1	AD	NK	SC	MD	NAE
Proposed	9.828	0.58442	.9925357	142	0.114019
Wiener	0.125	0.9800	1.185	198	0.15639

Thank you

THANK you !!!!