

Introduction to Image Interpolation and Super Resolution

Hsin-Hui Chen

**Digital Image and Signal Processing Lab
National Taiwan University**

Outline

- Introduction
- Image interpolation
 - Example1: New-edge directed interpolation (NEDI)
 - Example2: Soft-decision adaptive interpolation (SAI)
 - Example3: Adaptive Wiener Filter (AWF)
- Super resolution
 - Example1: Iterative back-projection (IBP)
 - Example2: Bilateral back-projection (BFIBP)
- Conclusions
- References

Introduction

- Applications
- Why image interpolation and super resolution matters?
- The difference between image interpolation and super resolution
- Classification of the image interpolation and super resolution

Applications

- HDTV
- Image/Video Coding
- Image/Video Resizing
- Image Manipulation
- Face Recognition
- View Synthesis
- Surveillance

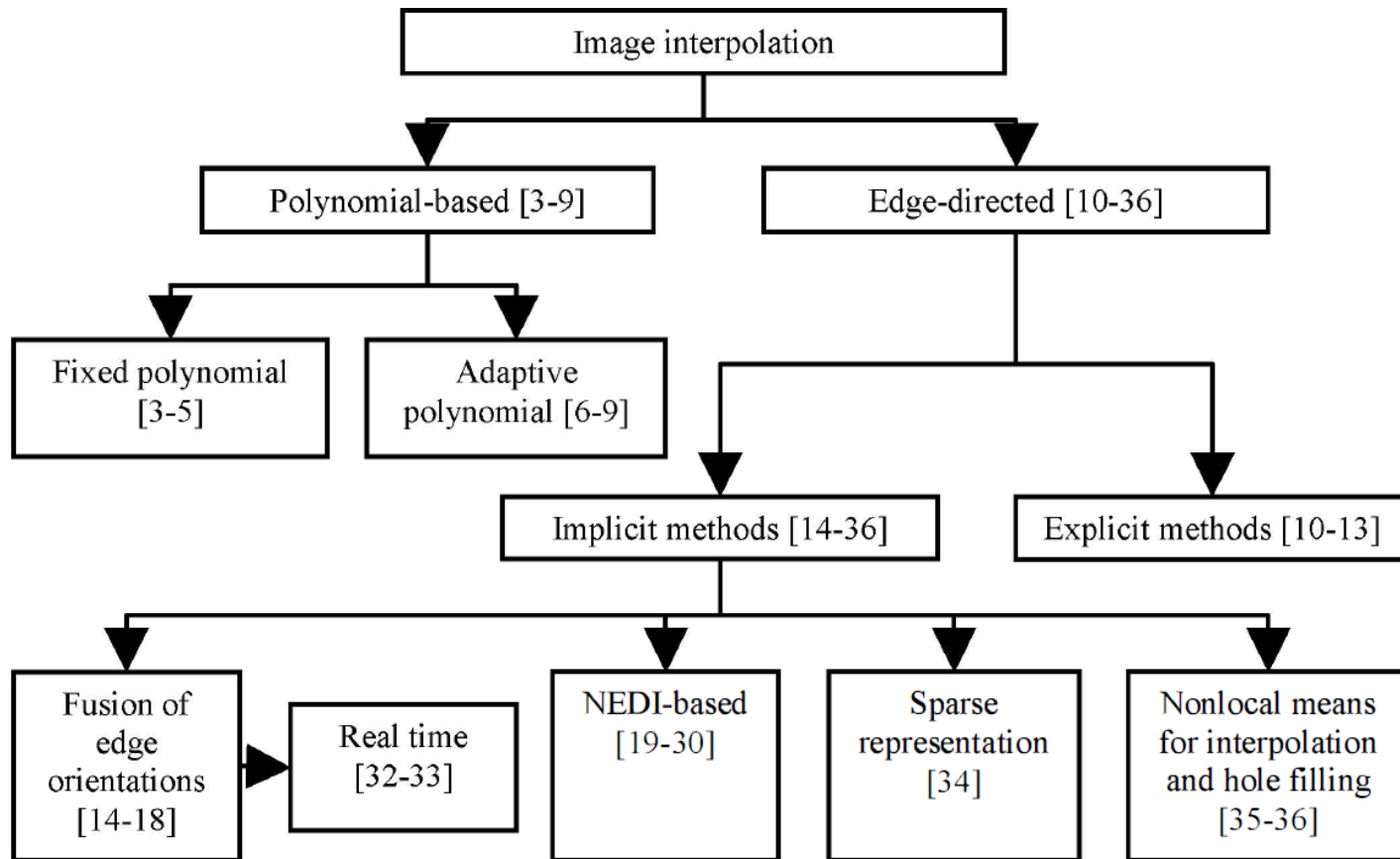
Why image interpolation and super resolution matters?

- Storage limitation
- Limited computational power
- Cost of camera
- Insufficient bandwidth (Limited network bandwidth)

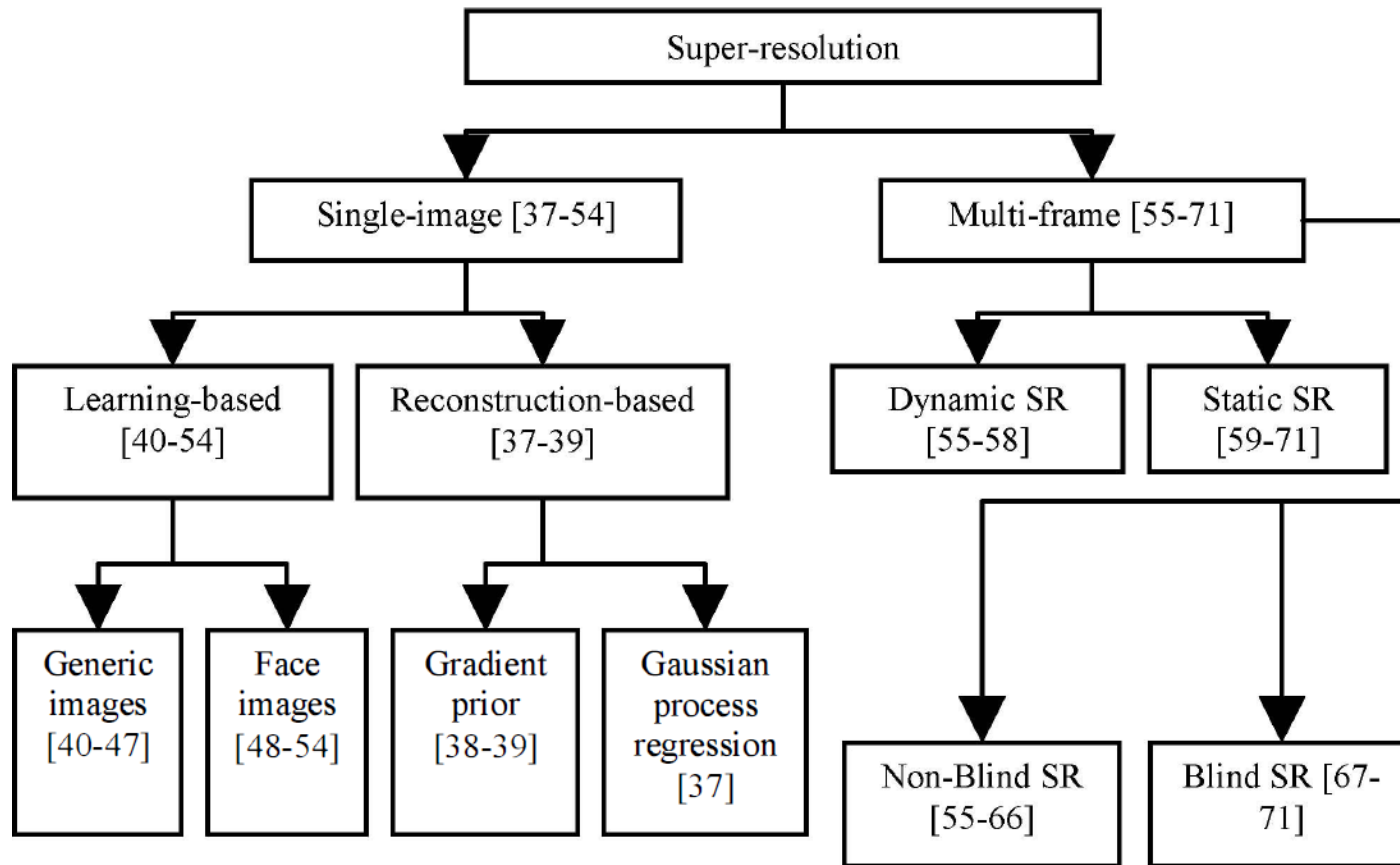
The difference between interpolation and super resolution

- **Interpolation** only involves upsampling the low-resolution image, which is often assumed to be aliased due to direct down-sampling.
- **Super resolution** aims to address undesirable effects, including the resolution degradation, blur and noise effects. Super resolution usually involves three major processes which are upsampling (interpolation), deblurring, and denoising.

Classification of Image Interpolation

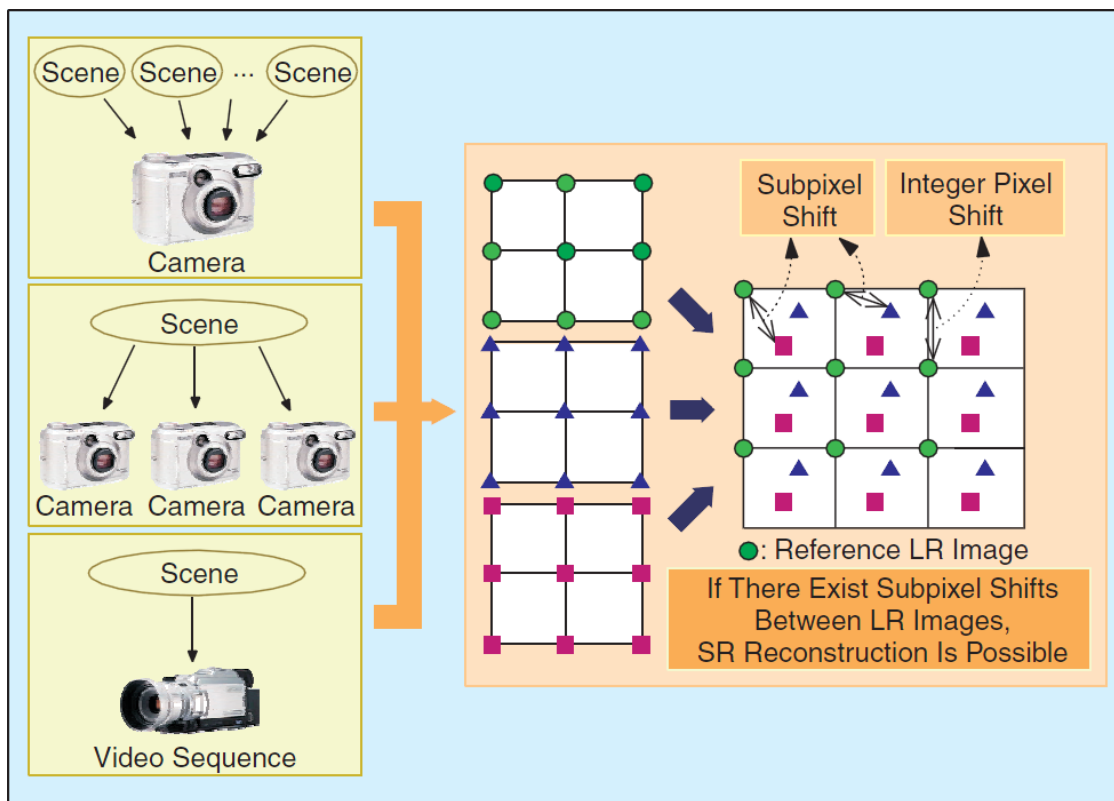


Classification of Super Resolution



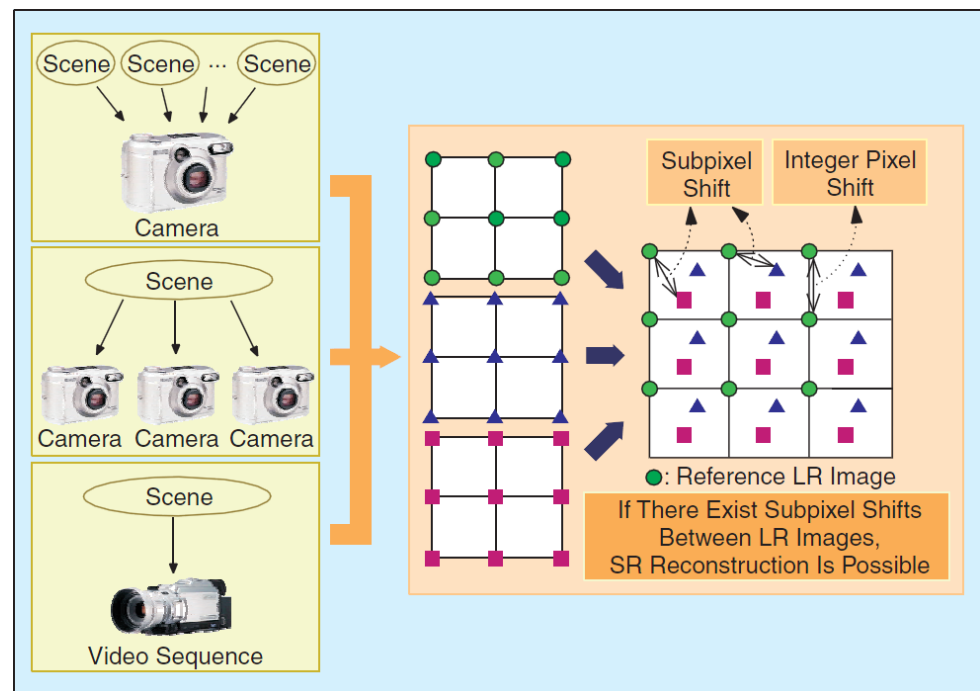
Basic Premise for Super Resolution

- How can we obtain an HR image from multiple LR images?
- **Basic premise:** The availability of multiple LR images captured from the same scene.

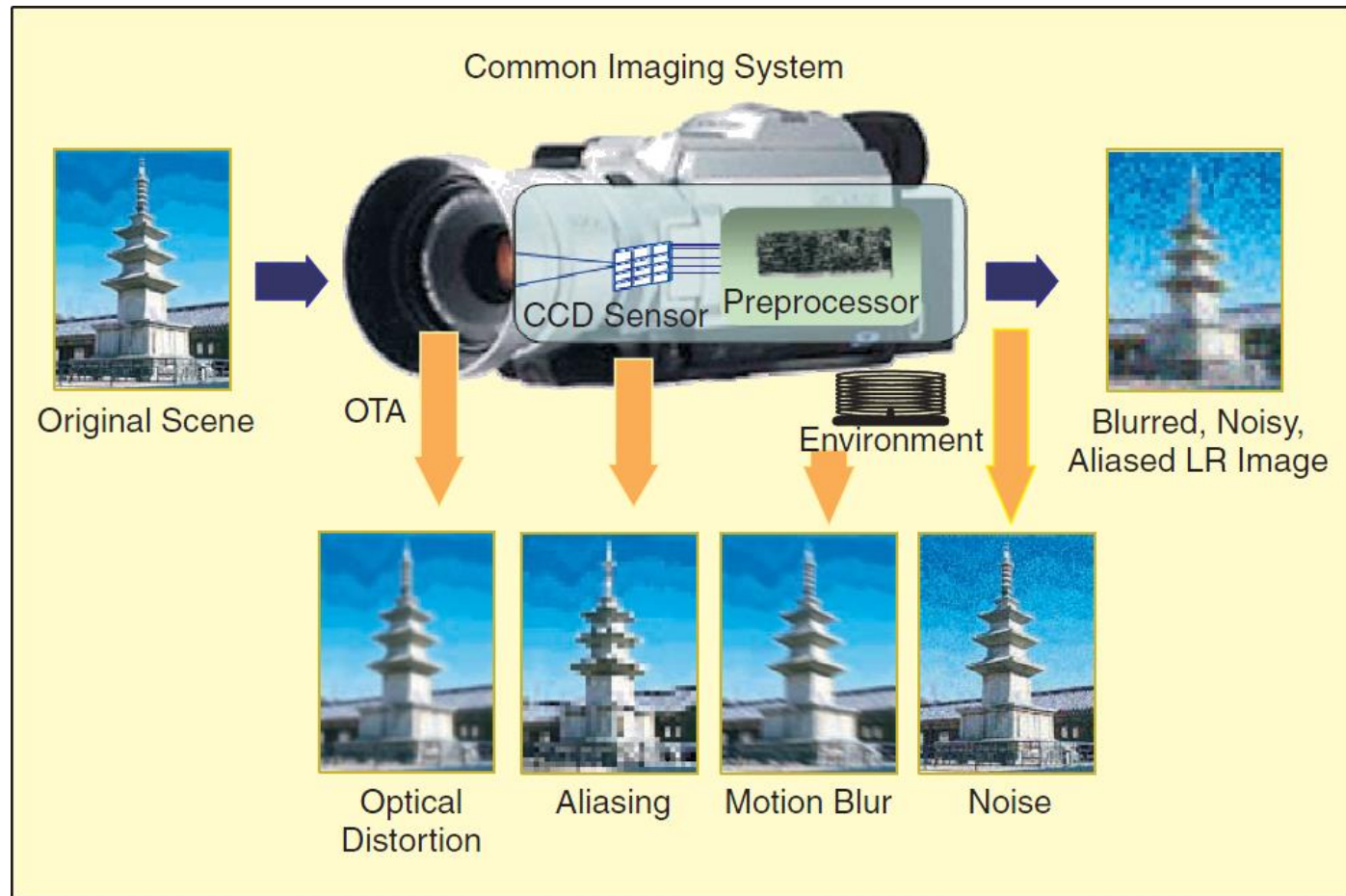


Basic Premise for Super Resolution

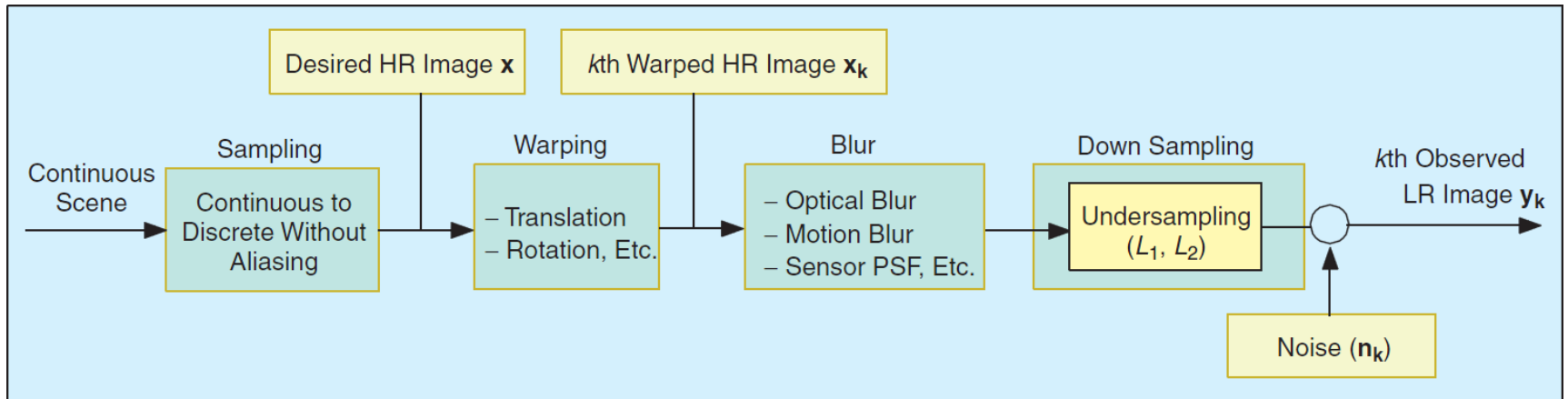
- Scene motions can occur due to the controlled or uncontrolled motions in imaging systems.
- If these scene motions are known or can be estimated within subpixel accuracy and if combine these LR images, SR image reconstruction is possible.



Common Image Acquisition System



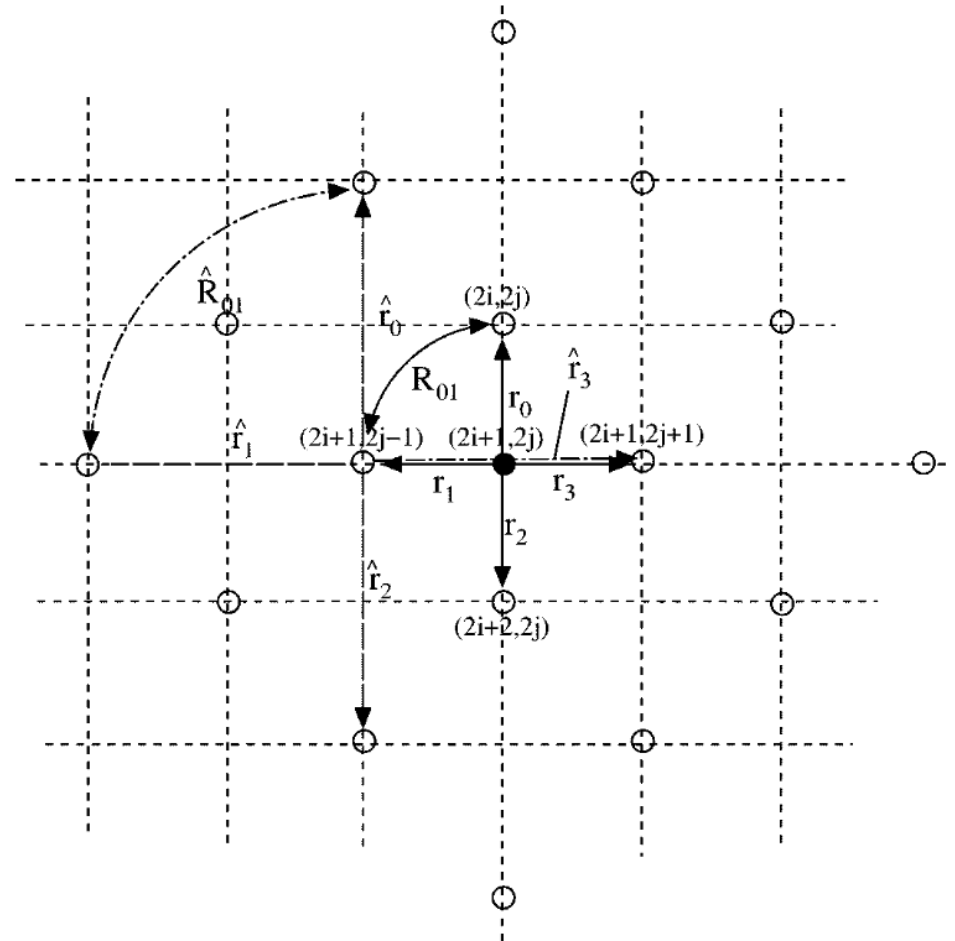
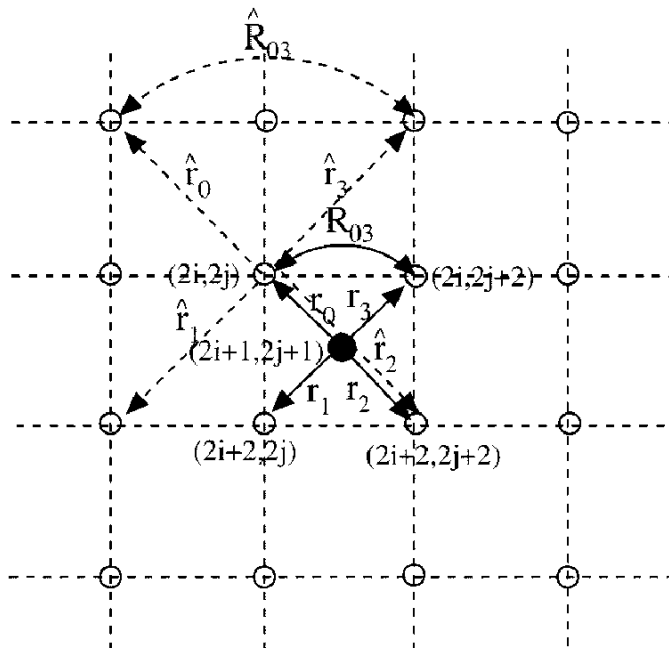
Observation Model



$$\mathbf{y}_k = \mathbf{D} \mathbf{B}_k \mathbf{M}_k \mathbf{x} + \mathbf{n}_k \quad \text{for } 1 \leq k \leq p$$

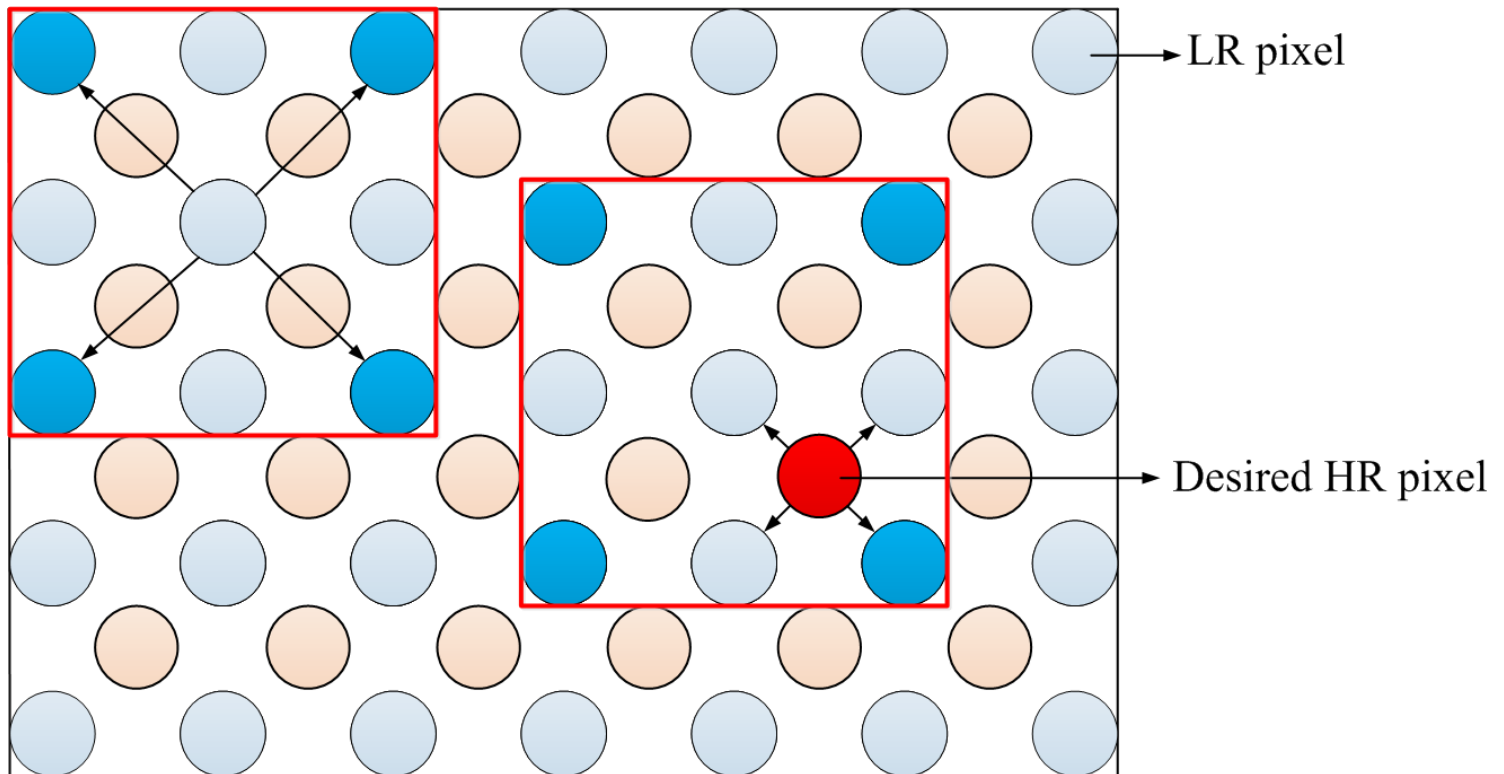
New Edge-Directed Interpolation

- Geometric duality

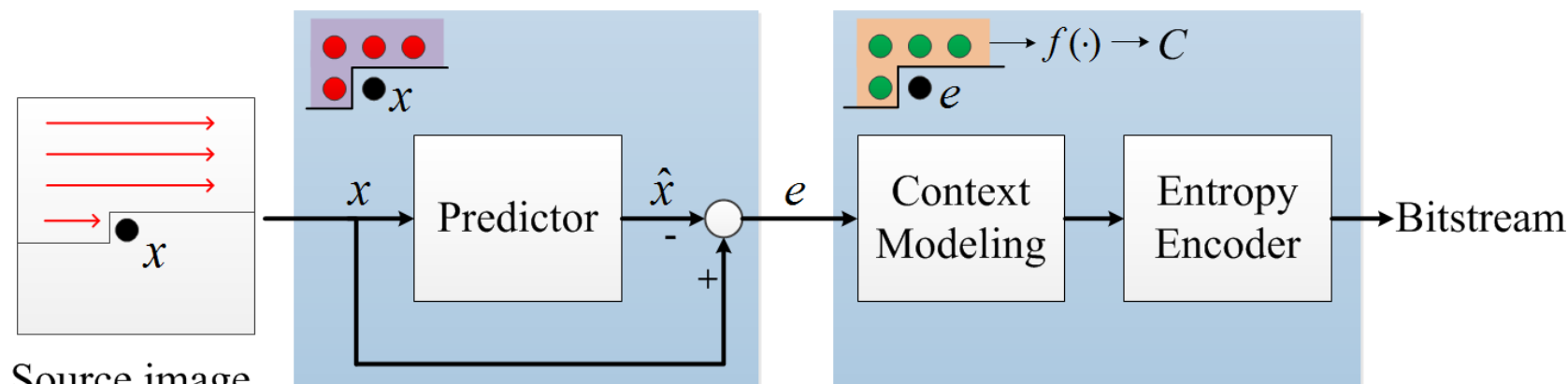
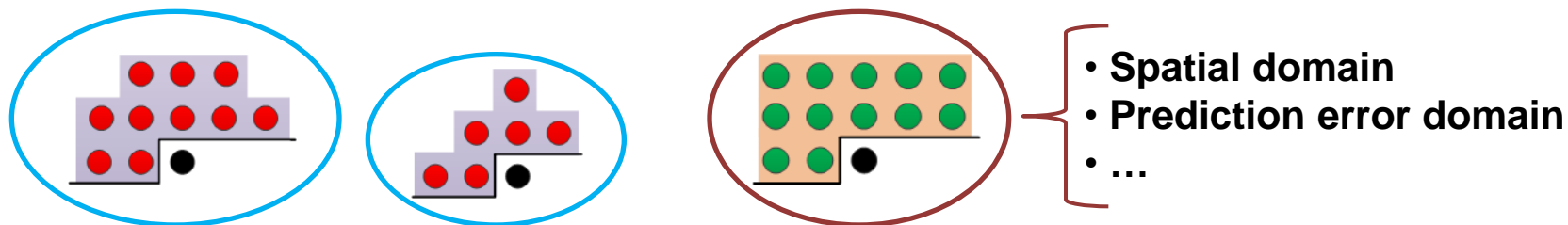


New Edge-Directed Interpolation

- Training window



Lossless image coding system



- **MED** (JPEG-LS)
- **GAP** (CALIC)
- **EDP**
- **Hybrid Predictor**

$p(e)$ → $p(e|c_1)$ → Arithmetic coding
 $p(e|c_2)$ → Arithmetic coding
 $p(e|c_3)$ → Arithmetic coding
 $p(e|c_4)$ → Arithmetic coding
 ...

New Edge-Directed Interpolation

- Consider the N nearest neighbors, which are the supports of the predictor, the value of the current pixel $X(n)$ can be predicted by

$$\hat{X}(n) = \sum_{k=1}^N a_k X(n-k)$$

where a_k is the prediction coefficient of the neighbor $X(n-k)$.

New Edge-Directed Interpolation

- To determine the coefficients a_k , LS optimization is used for minimizing

$$\|\vec{y} - C\vec{a}\|_2^2$$

where $\vec{a} = [a_1, a_2, \dots, a_N]^T$

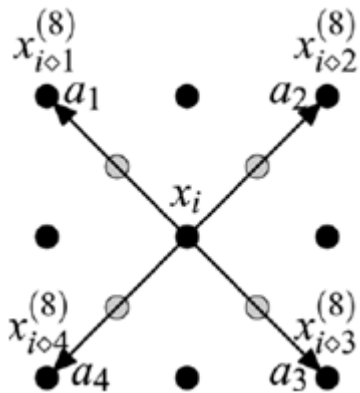
New Edge-Directed Interpolation

- The optimal coefficient vector can be solved from

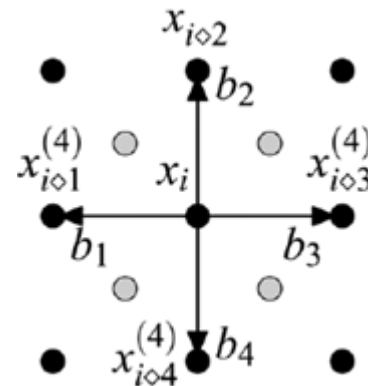
$$\vec{a} = (\mathbf{C}^T \mathbf{C})^{-1} (\mathbf{C}^T \vec{y})$$

Soft-decision adaptive interpolation

- Sample relations in estimating model



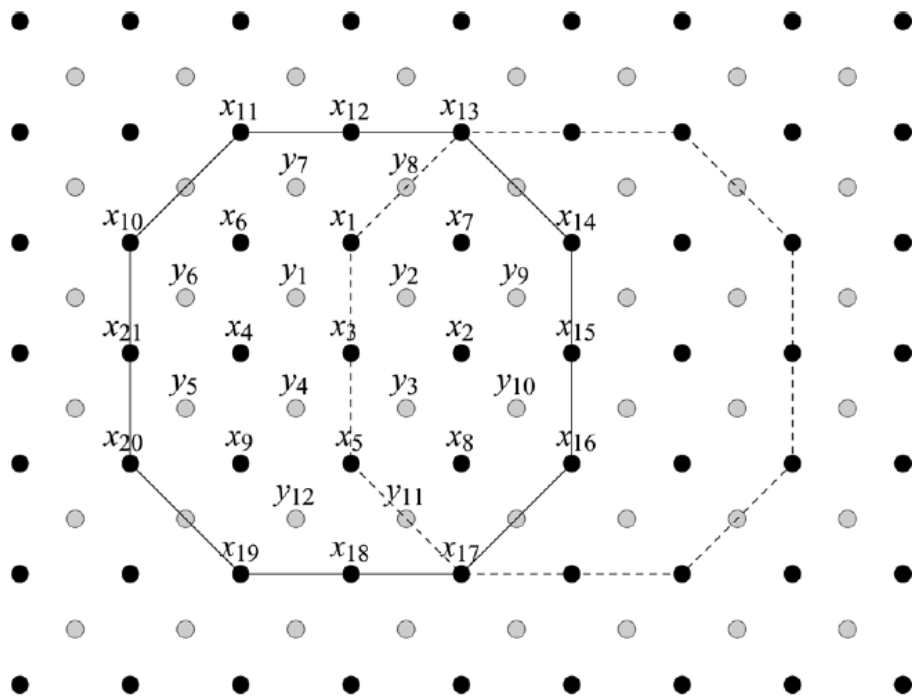
$$\hat{\mathbf{a}} = \arg \min_{\mathbf{a}} \sum_{i \in W} \left(x_i - \sum_{1 \leq t \leq 4} a_t x_{i \diamond t}^{(8)} \right)^2$$



$$\hat{\mathbf{b}} = \arg \min_{\mathbf{b}} \sum_{i \in W} \left(x_i - \sum_{1 \leq t \leq 4} b_t x_{i \diamond t}^{(4)} \right)^2$$

Soft-decision adaptive interpolation

- Existing interpolation methods estimate each missing pixel independently from others, which is called “**hard-decision**”
- A new strategy of “**soft-decision**” estimation is adopted

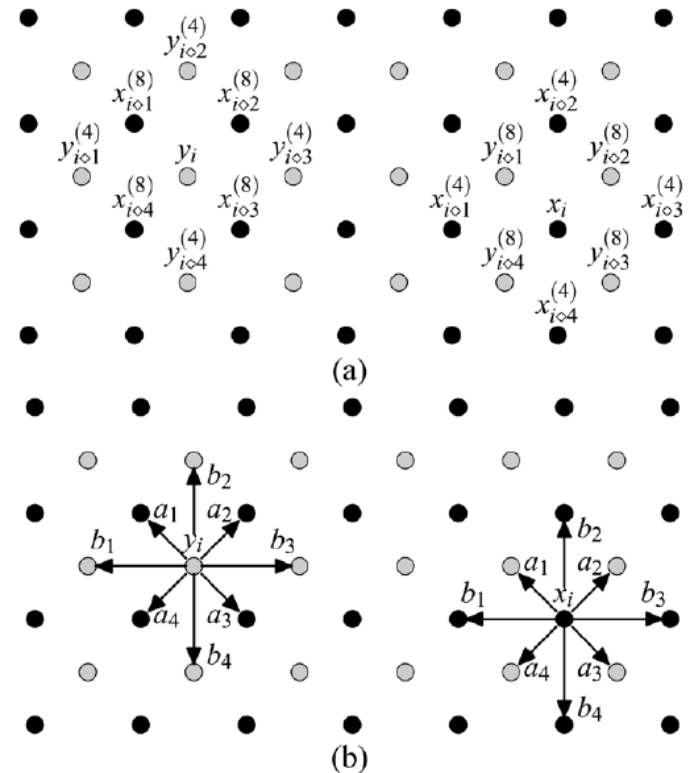


Soft-decision adaptive interpolation

- Existing interpolation methods estimate each missing pixel independently from others, which is called “**hard-decision**”
- A new strategy of “**soft-decision**” estimation is adopted

$$y_i = \sum_{1 \leq t \leq 4} a_t x_{i \diamond t}^{(8)} + v_i$$

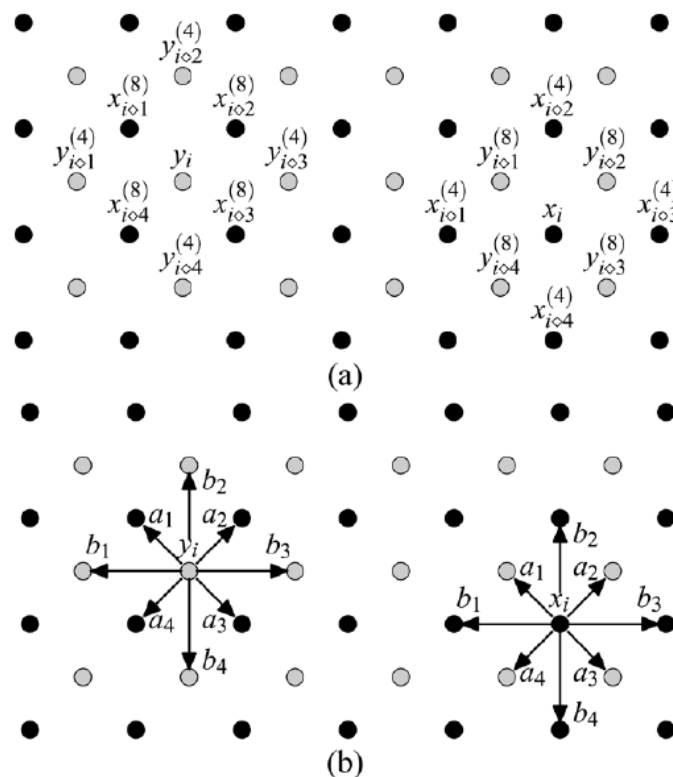
$$\hat{\mathbf{y}} = \arg \min_{\mathbf{y}} \left\{ \sum_{i \in W} \left\| y_i - \sum_{1 \leq t \leq 4} a_t x_{i \diamond t}^{(8)} \right\| + \sum_{i \in W} \left\| x_i - \sum_{1 \leq t \leq 4} a_t y_{i \diamond t}^{(8)} \right\| \right\}$$



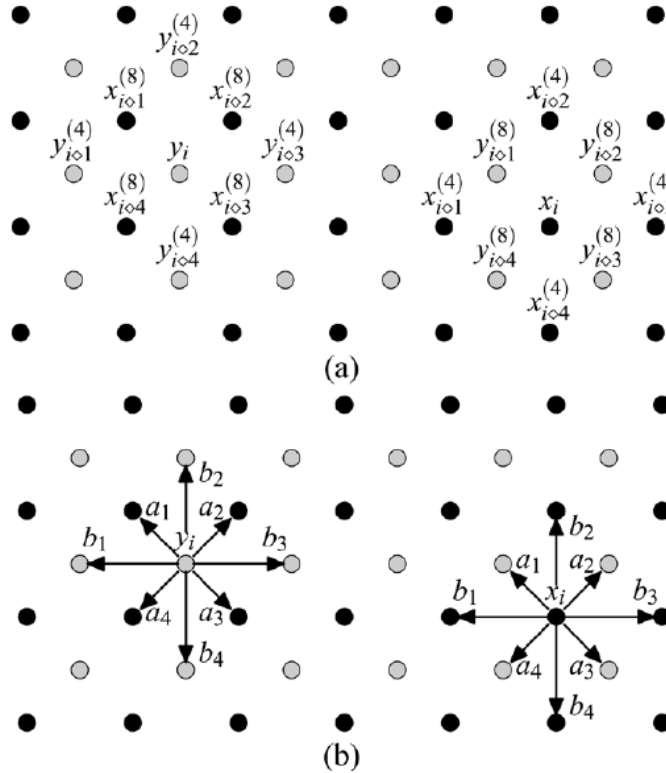
Soft-decision adaptive interpolation

- Include horizontal and vertical correlations

$$y_i = \sum_{1 \leq t \leq 4} \|b_t y_{i \diamond t}^{(4)}\| + v_i$$



Soft-decision adaptive interpolation



$$J(\lambda) = \min_{\mathbf{y}} \left\{ \sum_{i \in W} \left\| y_i - \sum_{1 \leq t \leq 4} a_t x_{i\odot t}^{(8)} \right\| + \sum_{i \in W} \left\| x_i - \sum_{1 \leq t \leq 4} a_t y_{i\odot t}^{(8)} \right\| + \lambda \sum_{i \in W} \left\| y_i - \sum_{1 \leq t \leq 4} b_t y_{i\odot t}^{(4)} \right\| \right\}$$

subject to $\sum_{i \in W} \left\| y_i - \sum_{1 \leq t \leq 4} b_t y_{i\odot t}^{(4)} \right\| \approx \sum_{i \in W} \left\| x_i - \sum_{1 \leq t \leq 4} b_t x_{i\odot t}^{(4)} \right\|$

Original image



Bicubic



NEDI



SAI



Original image



Bicubic



NEDI



SAI



Original image



Bicubic



NEDI

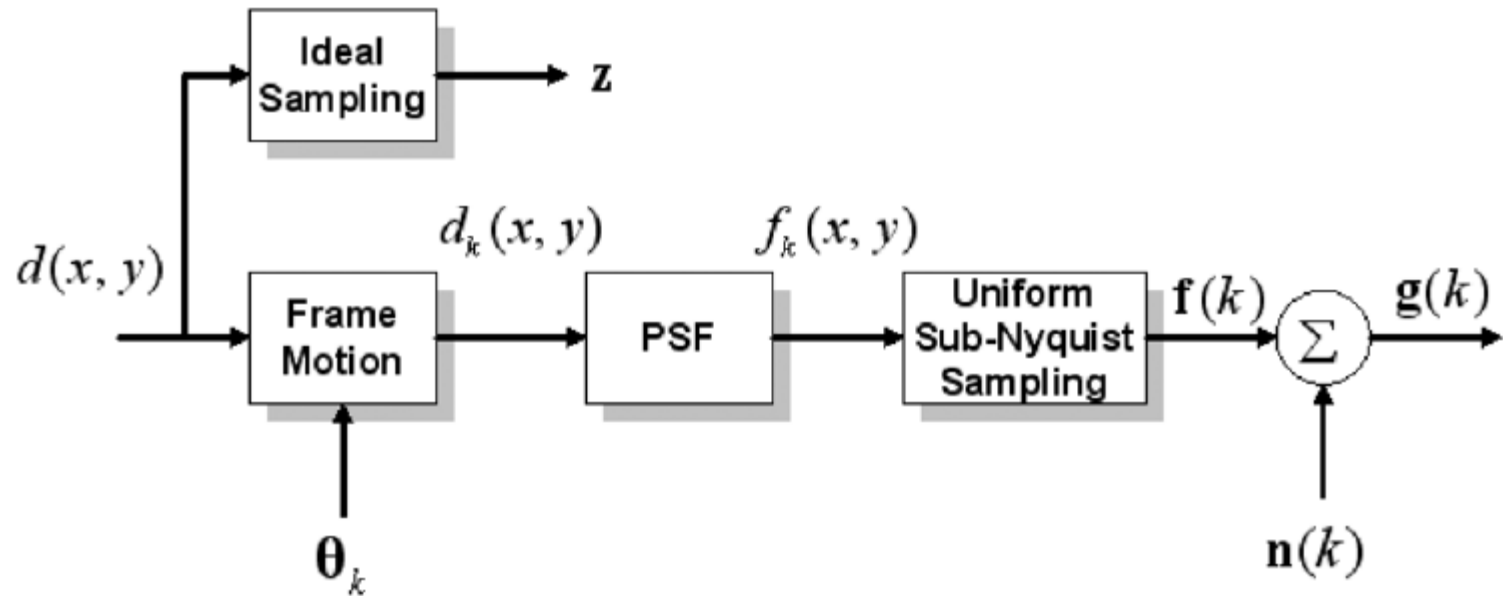


SAI



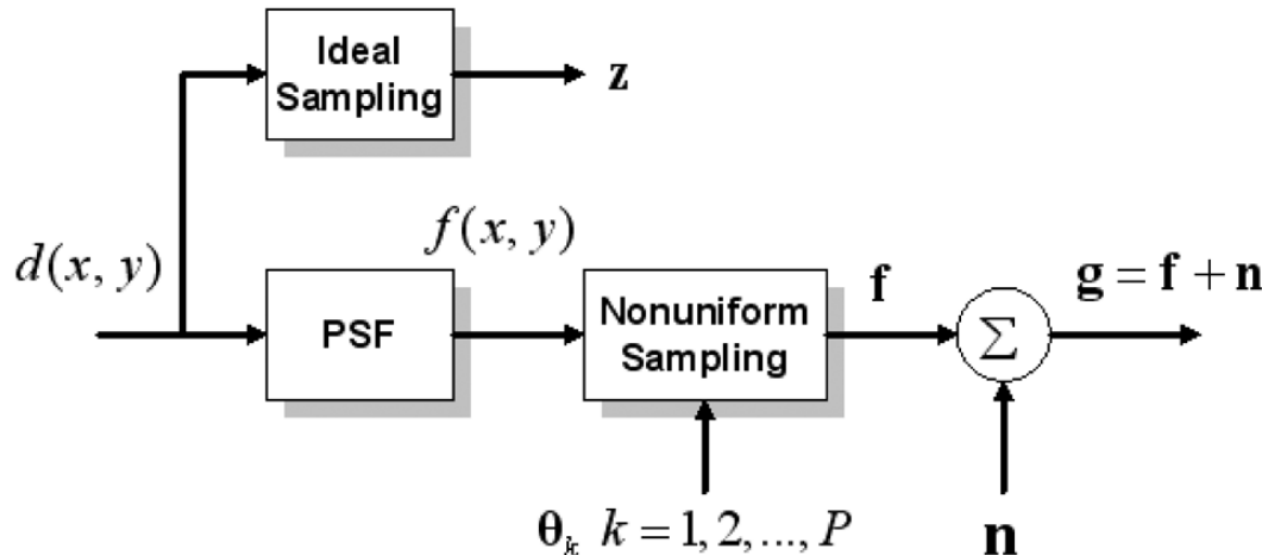
Adaptive Wiener Filter

- Observation model relating a desired 2-D continuous scene, $d(x,y)$, with a set of corresponding LR frames



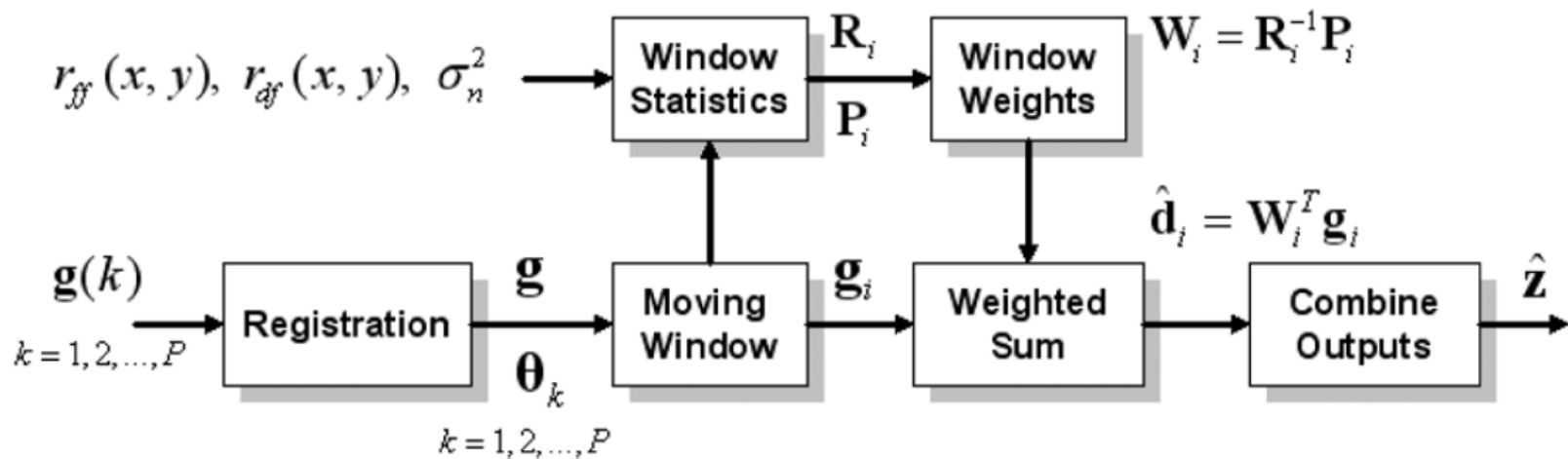
Adaptive Wiener Filter

- Alternative observation model

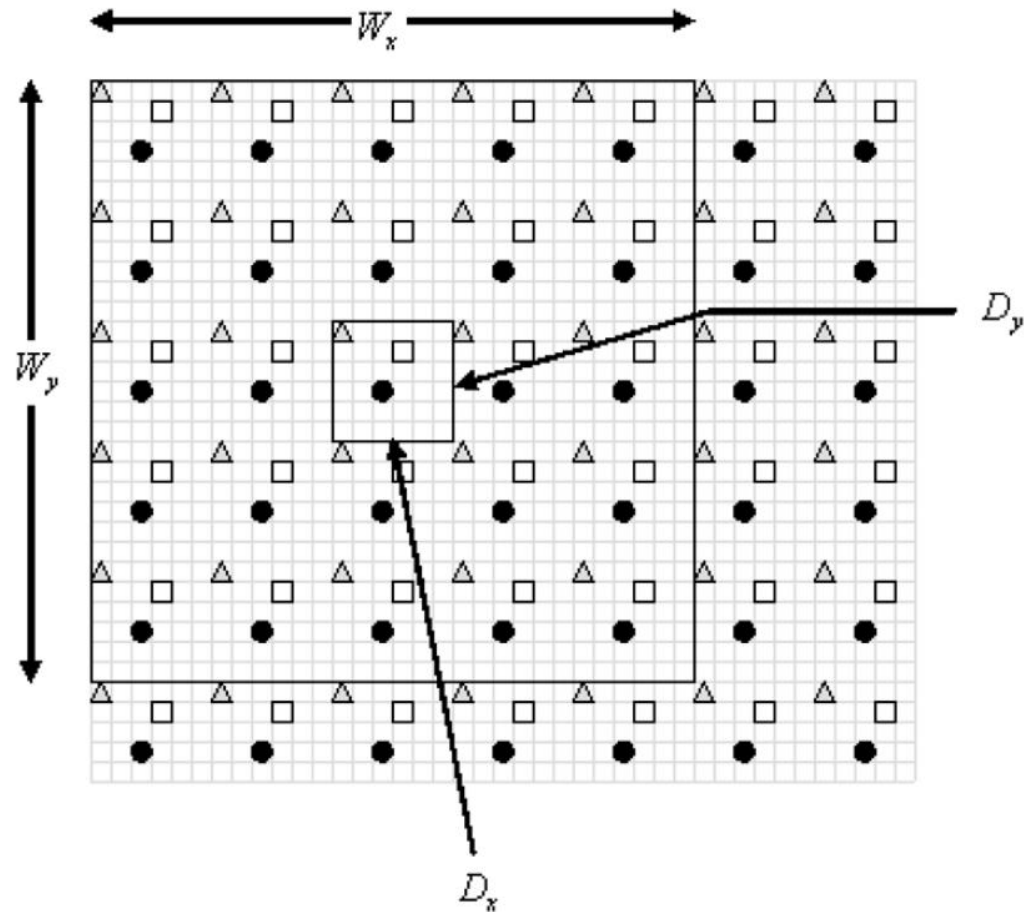


Adaptive Wiener Filter

- Overview of the proposed SR algorithm



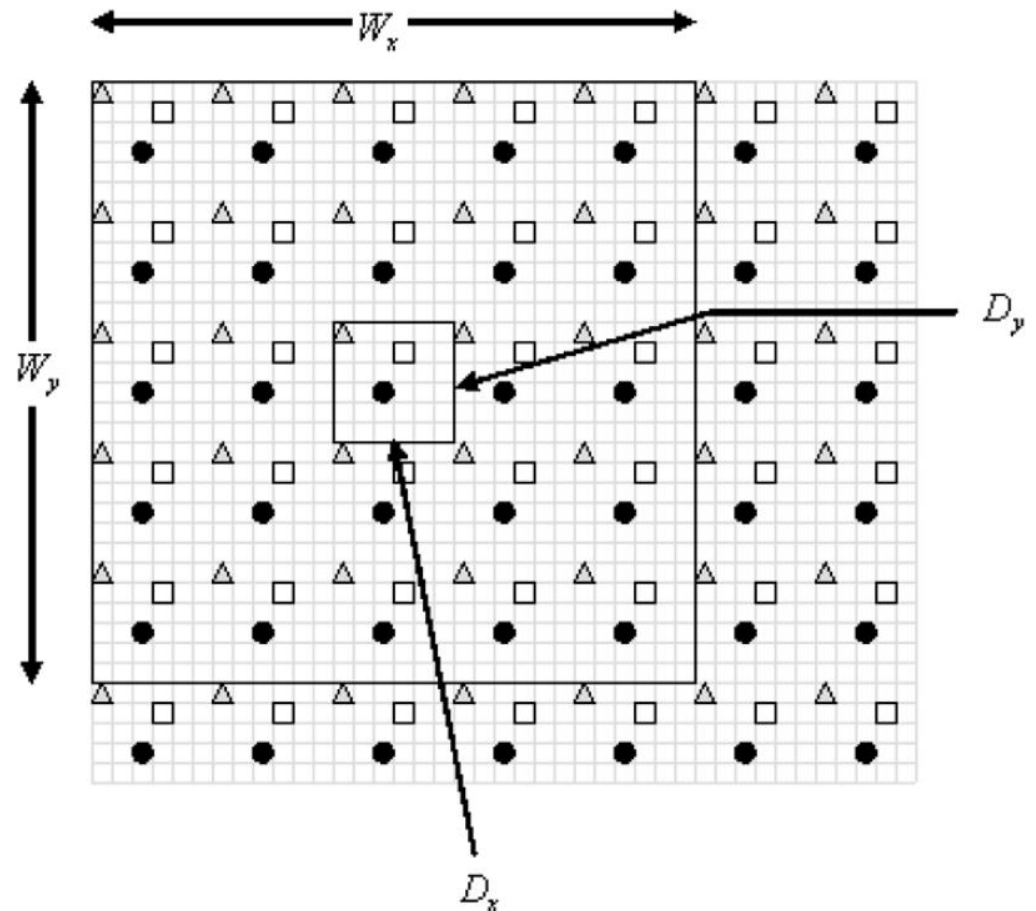
Adaptive Wiener Filter



Adaptive Wiener Filter

$$\hat{\mathbf{d}}_i = \mathbf{W}_i^T \mathbf{g}_i$$

$$\mathbf{W}_i = \mathbf{R}_i^{-1} \mathbf{P}_i$$



Iterative Back-Projection

- The formulation of an LR image from the unknown HR image can be formulated as follows:

$$\mathbf{I}^l = (\mathbf{I}^h * g) \downarrow_s$$

where \mathbf{D} is the down-sampling matrix, and \mathbf{G} is the point spread function (PSF) which is generally a smoothing kernel.

Iterative Back-Projection

- The underlying criterion is that the reconstructed HR image should produce the same LR image if passing it through the same image formation process.

$$\mathbf{I}^l = (\mathbf{I}^h * g) \downarrow_s$$

Iterative Back-Projection

- The reconstruction error is defined as

$$e_r(\mathbf{I}) = \mathbf{I}^l - (\mathbf{I} * g) \downarrow_s$$

Iterative Back-Projection

- Given an LR image, the updating procedure can be summarized as follows

- Compute the LR error $\mathbf{e}_r(\mathbf{I}_t^h)$ by $\mathbf{e}_r(\mathbf{I}) = \mathbf{I}^l - (\mathbf{I} * g) \downarrow_s$
- Update the HR image by back-projecting the error as follows

$$\mathbf{I}_{t+1}^h = \mathbf{I}_t^h + \mathbf{e}_r(\mathbf{I}_t^h) \uparrow_s * p.$$

Bilateral Back-Projection

Theorem 1 *By updating the HR image with the back-projection iteration, \mathbf{I}_t^h will converge to a desired image \mathbf{I}^c , which satisfies Eqn. 1, with an exponential rate for all $s \geq 1$, given $\|\delta - g * p \downarrow_s\|_1 < 1$.*

Bilateral Back-Projection

- Bilateral filtering

$$\mathbf{h}(x) = \frac{1}{k(x)} \sum_y \mathbf{I}(y) c(x, y) s(\mathbf{I}(x), \mathbf{I}(y))$$

$$k(x) = \sum_y c(x, y) s(\mathbf{I}(x), \mathbf{I}(y))$$

Bilateral Back-Projection

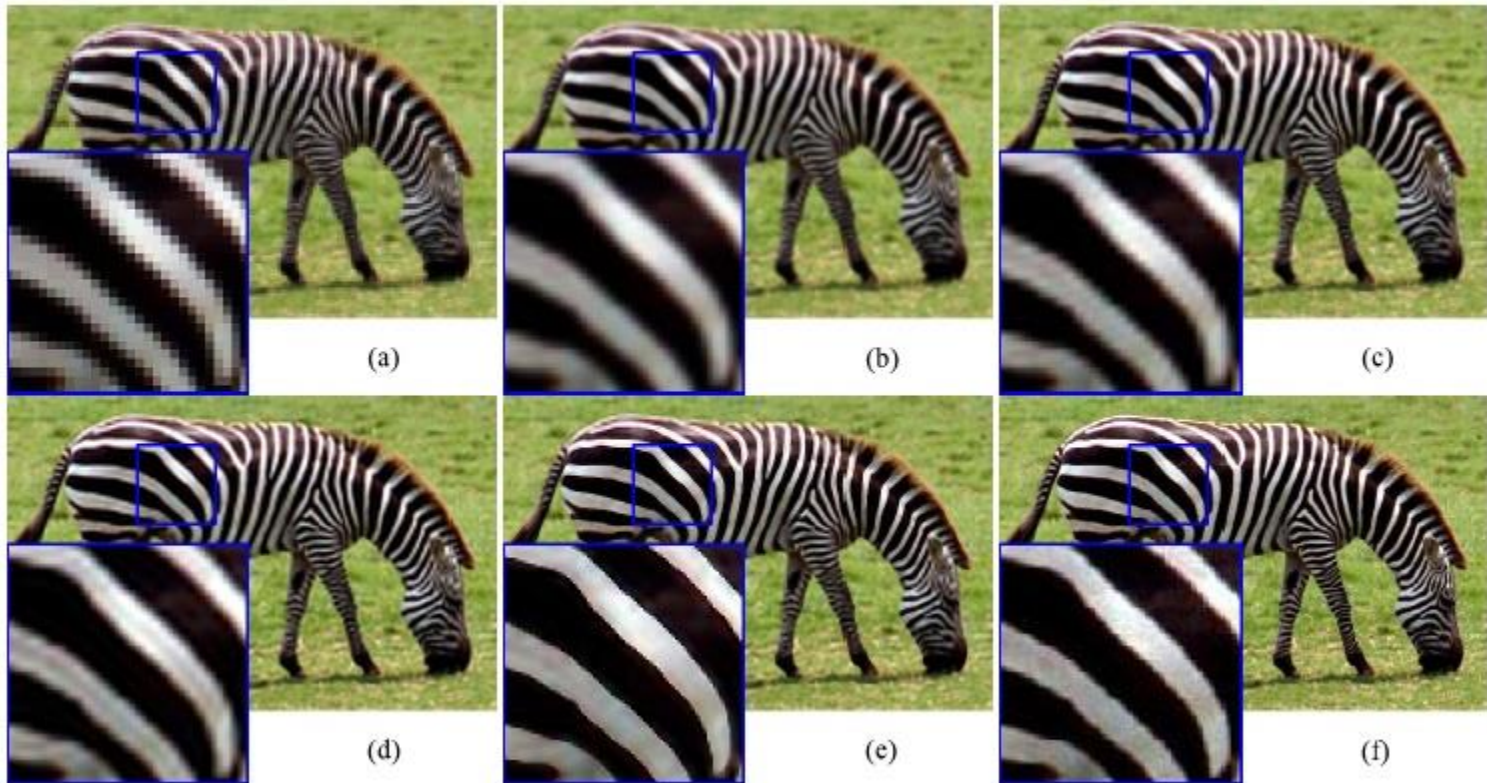
- Bilateral filtering

$$\mathbf{h}(x) = \frac{1}{k(x)} \sum_y \mathbf{I}(y) c(x, y) s(\mathbf{I}(x), \mathbf{I}(y))$$

$$c(x, y) = \exp\left(\frac{-\|x - y\|_2^2}{2\sigma_c^2}\right)$$

$$s(u, v) = \exp\left(\frac{-\|u - v\|_2^2}{2\sigma_s^2}\right)$$

Bilateral Back-Projection



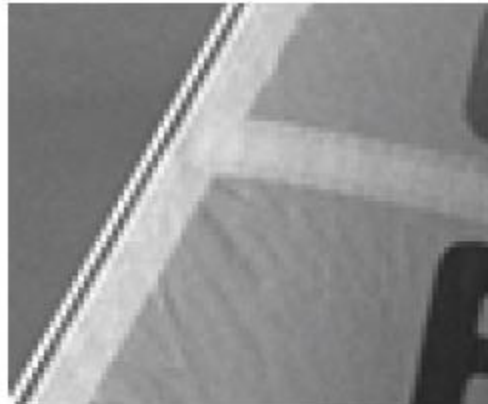
(a) LR input image (b) bicubic interpolation (c) sharpened bicubic (d) back-projection (e) bilateral BP (f) ground truth

Bilateral Back-Projection



More experiment results, the first row shows the LR input images, and the second row shows our results.

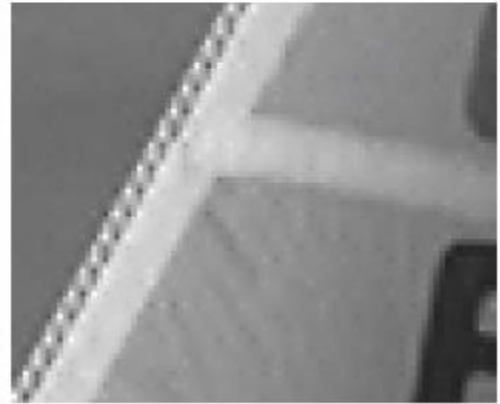
Bilateral Back-Projection



Bicubic



IBP



BFIBP

Bilateral Back-Projection



Bicubic



IBP



BFIBP

Thank You

Q & A