Super Resolution

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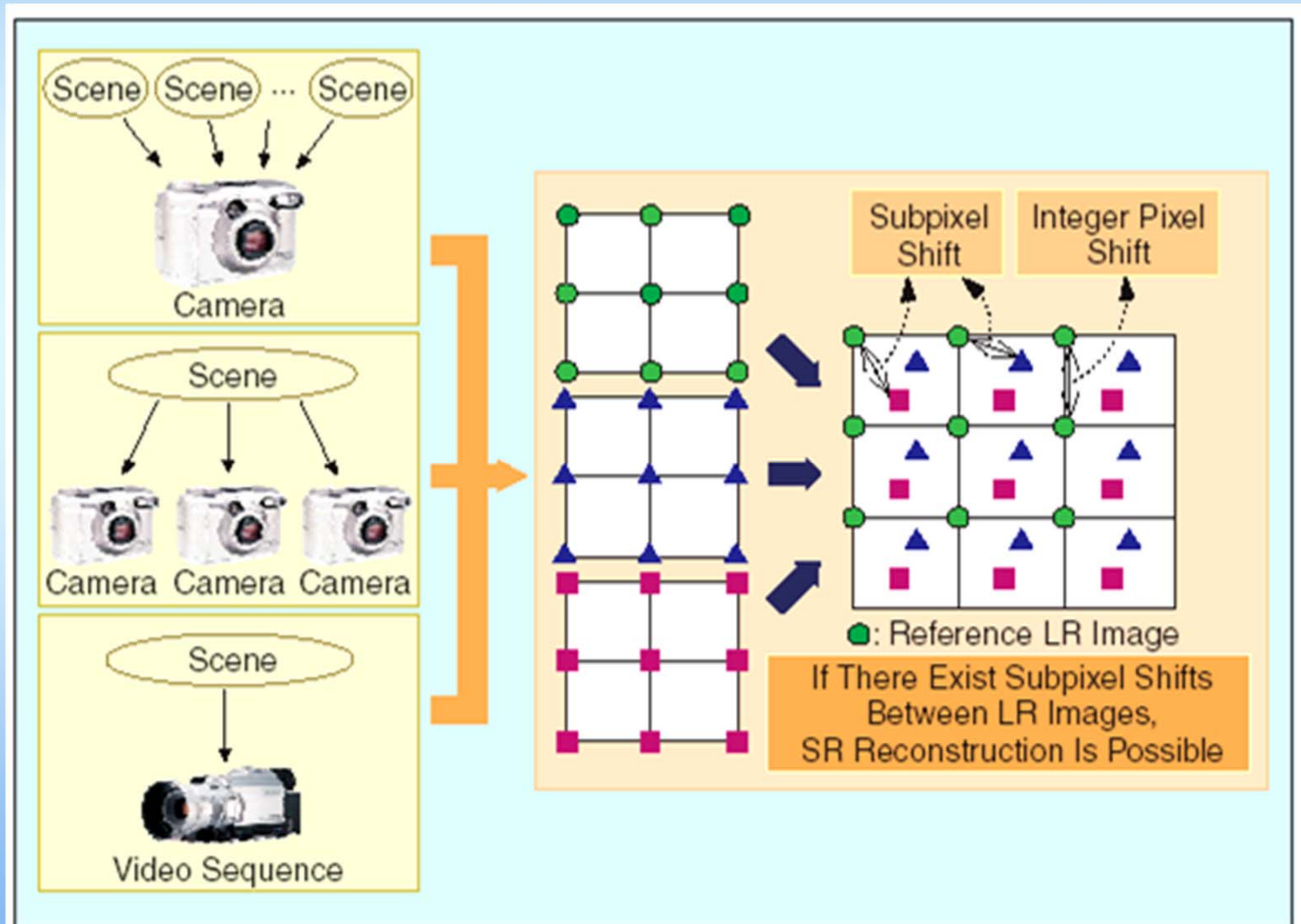
Super Resolution ? (I)

- Super Resolution (SR) is the process of obtaining the higher resolution information from low resolution observations
  - Simply Resolution Enhancement
- Super Resolution = Bandwidth Extrapolation
  - Recovering HF information
- Super resolution is different from
  - Interpolation
    - Single image
  - Restoration
    - Focus on point spread function

Super Resolution ? (II)

- Obtaining an HR image from LR images



Super Resolution ? (III)

- Example of SR

Super Resolution ? (IV)

- Comparison with interpolation

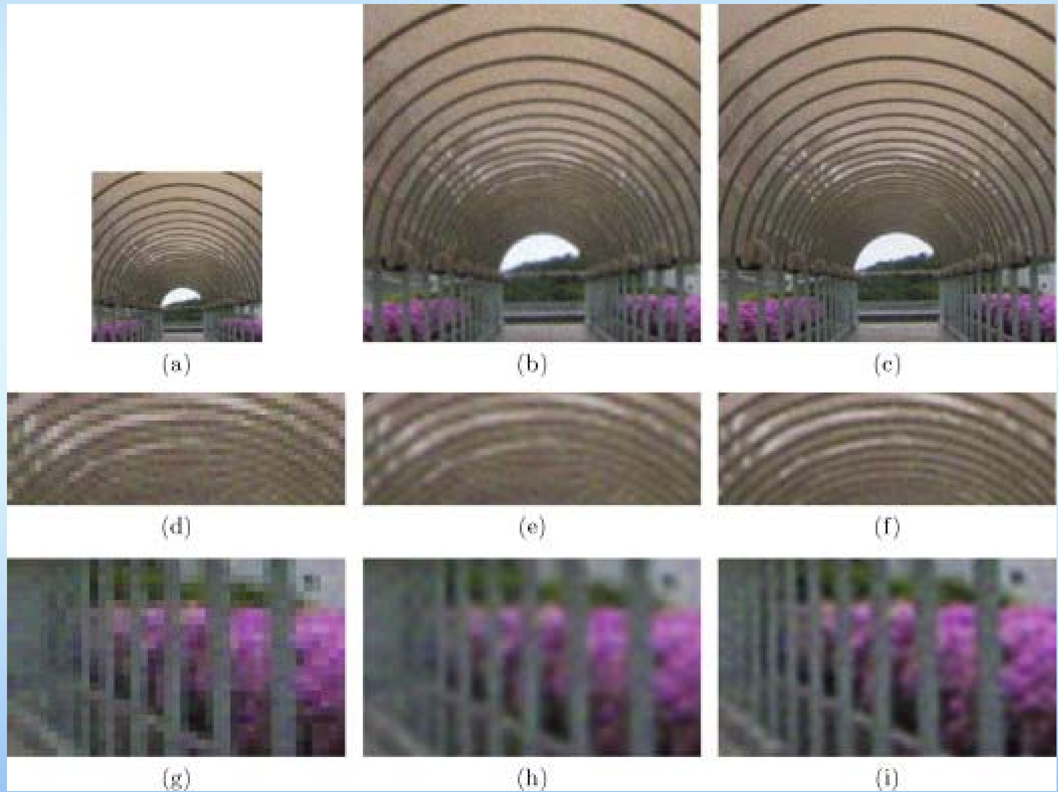
Zero-order interpolation

Bilinear interpolation

Super-resolution

Super Resolution ? (V)

- Comparison with interpolation



Zero-order interpolation　Bilinear interpolation　Super-resolution

Categories of SR (I)

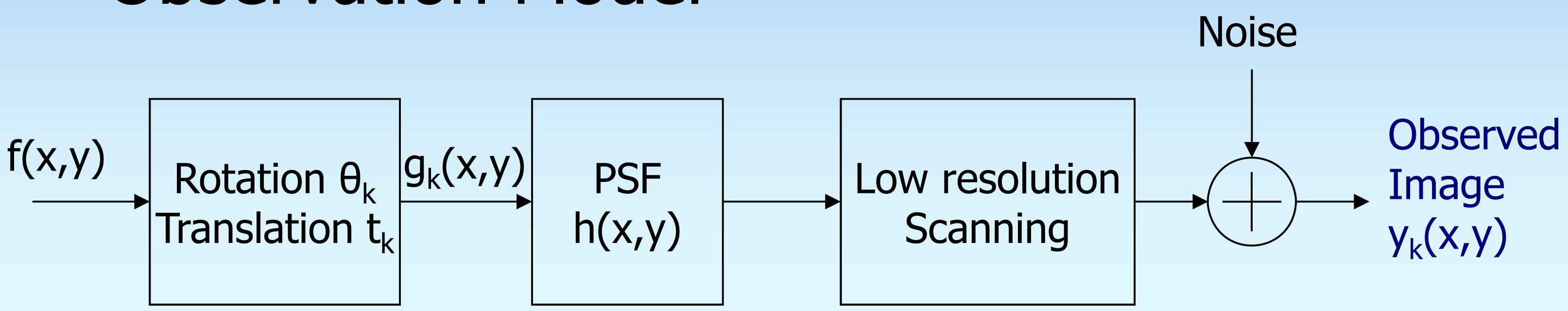
- Reconstruction-based SR
  - Based on sampling theories
  - Reconstruct the original from LR inputs
  - Most SR algorithms belong to this category
  - References
    - M.G. Kang, "Super resolution image reconstruction," *IEEE signal processing magazine*, pp. 21-36, May 2003.
    - M. Shah, A. Zahkor, "Resolution enhancement in color video sequences," IEEE IP, pp. 879-885, 1999. June.
    - Schultz and Stevenson, "Extraction of high resolution frames from video sequences," IEEE IP, vol. 5 pp. 996-1011, June 1996.

Categories of SR (II)

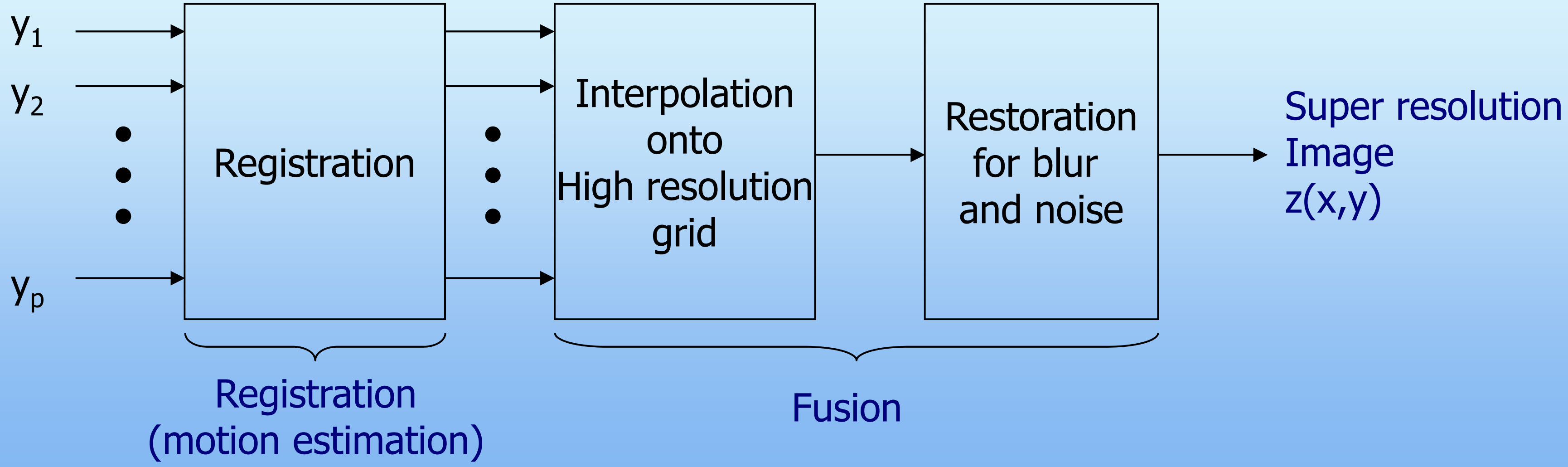
- Learning-based SR
  - Create the HR images based on learned generative models
  - Hallucination
    - Face, document image
  - References
    - "Face Hallucination"
      - Baker and Kanade (CVPR 2000)
      - Dedeoglu and Kanade (CVPR 2004)
    - Two-step approach to face hallucination: Liu (CVPR 2001)
    - Learning in low level vision: W. Freeman, E. Pasztor , IJCV vol. 40(1), pp.25-47, 2000.

Reconstruction-based SR (I)

- Observation Model



- Super resolution scheme



Reconstruction-based SR (II)

- Formulation

$$\mathbf{y}_k = D_k C_k F_k \mathbf{z} + \mathbf{n}_k$$

$$\mathbf{y} = \mathbf{Hz} + \mathbf{n}$$

y : observed LR image(N_1xN_2)
z : HR image (ref. frame)(qN_1xqN_2)
n : additive noise
(white Gaussian with zero mean)
F : geometric warp matrix
C : blurring matrix
D : decimation matrix

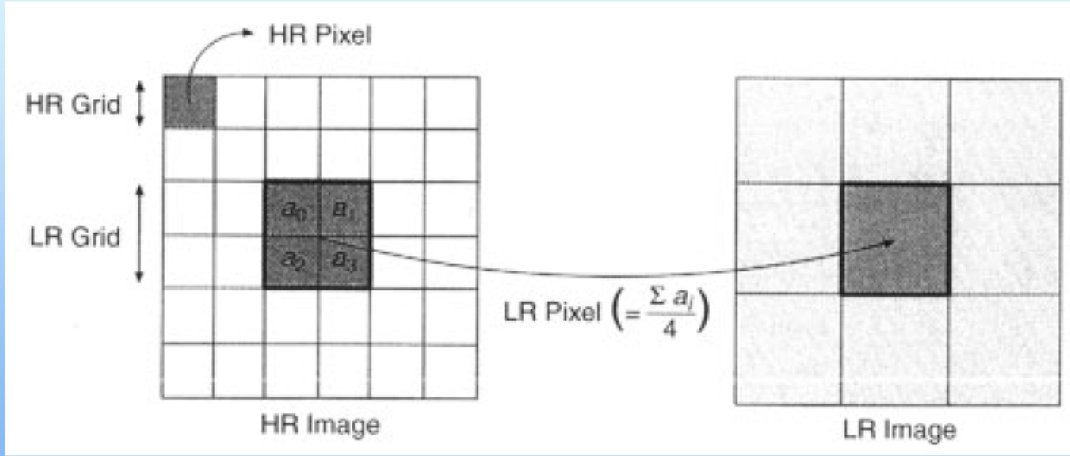
- Reconstruction constraints
  - HR images must be very close to the input image when smoothed and down-sampled
- SR is an ill-posed inverse problem
  - Regularization is needed
    - Deterministic, Stochastic Regularization
    - Use a-priori information about the solution

Reconstruction-based SR (III)

- PSF model between LR and HR images
  - Considering optical system
  - EX: out-of-focus, different sensor size

$$\mathbf{y}_k = \underline{D_k C_k} F_k \mathbf{z} + \mathbf{n}_k$$

$$\mathbf{y} = \mathbf{H}\mathbf{z} + \mathbf{n}$$



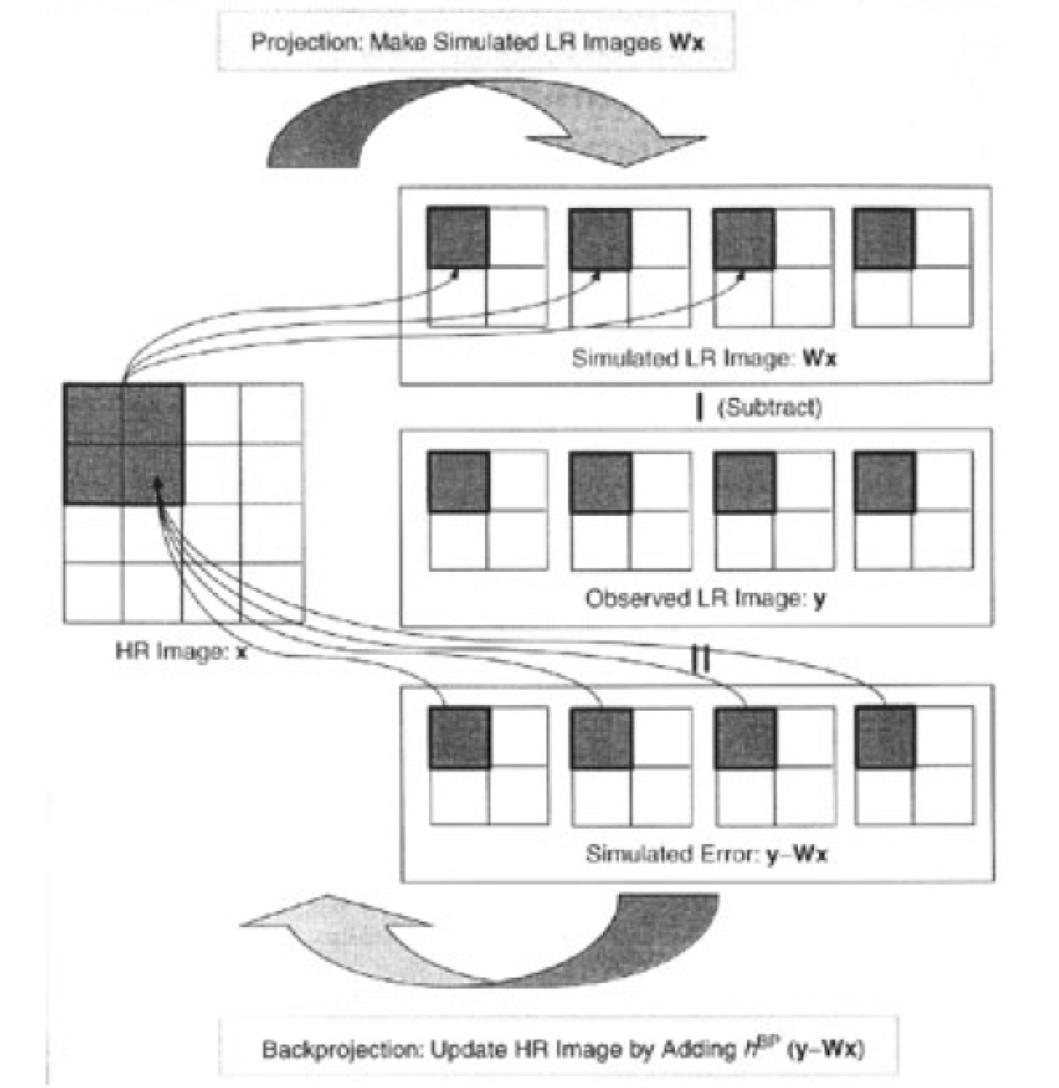
Reconstruction-based SR (IV)

- Non-uniform interpolation
  - Registration, interpolation, restoration(debluring)
- Projection onto convex set (POCS)
  - Iterative projection onto prior set
- Frequency domain approach
  - De-aliasing between CFT of HR image and DFT of LR image
- Regularized reconstruction
  - Deterministic (CLS) method
  - Bayesian (MAP) method

POCS approach

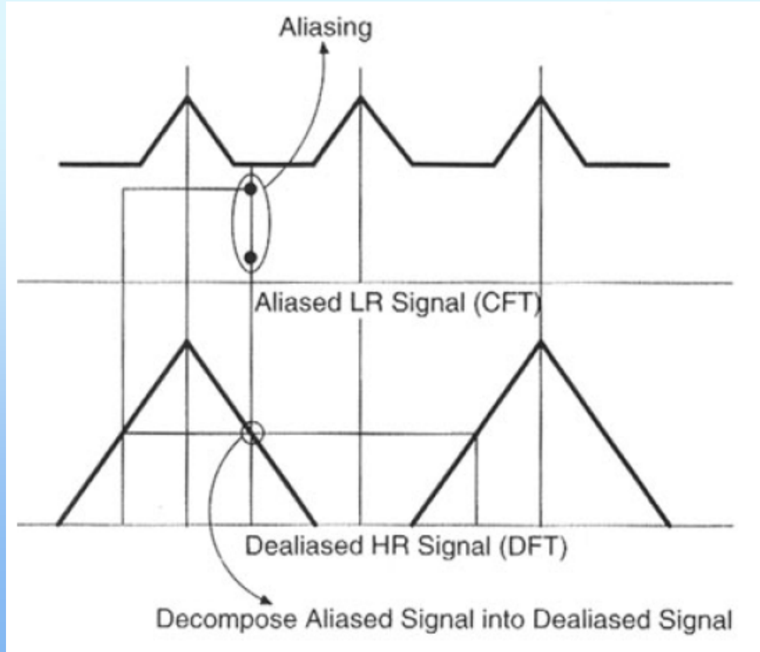
- Iterative projection on prior conditions (convex set)

$$x^{n+1} = P_m P_{m-1} \ldots P_2 P_1 x^n$$



Frequency Domain Approach

- Considering the difference between FT between HR and LR images.
- Reconstruct the aliased high frequency components in the frequency domain

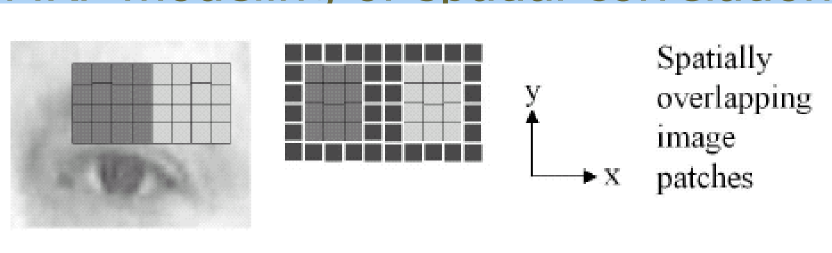


Limits on Reconstruction-based SR

- Regularization makes reconstructed HR image too smooth.
- Limited motion model
  - Affine, geometric polynomial transformation
- Blurring process is unknown
- Registration errors
  - Incorrect motion vectors
- Limited magnification factor
  - Less than 4 times enlargement

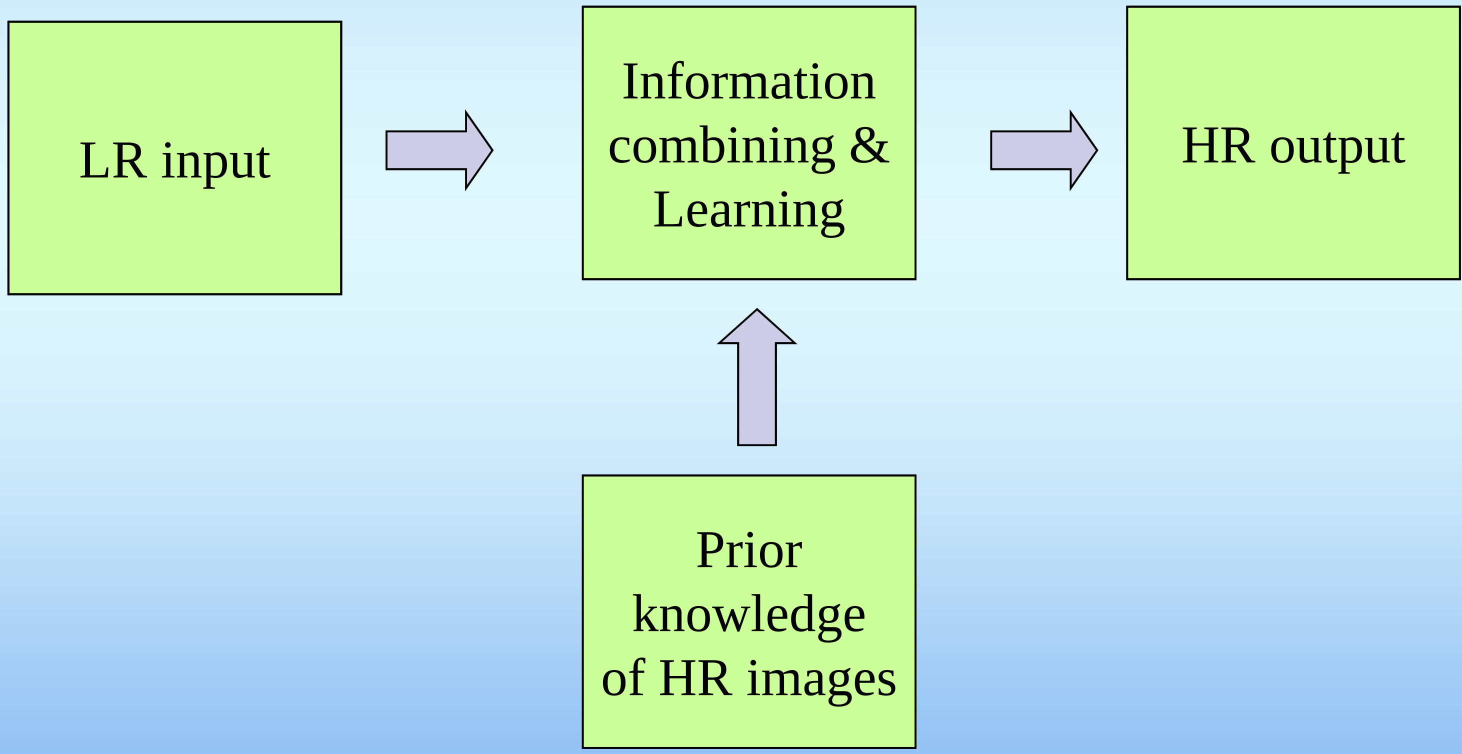
Learning-based SR (I)

- Motivations
  - Limits on reconstruction-based SR
  - The specific class of images can be better modelled.
    - Face images, documents
    - Much larger magnification factor: 8, 16…
- Bayesian MAP Framework
  - Likelihood function
  - Prior model
    - Recognition-based prior knowledge of HR images
    - MRF modeling of spatial correlation



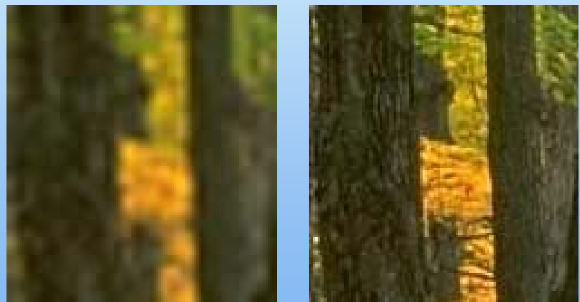
Learning-based SR (II)

- SR as recognition process



EX: Learning-based SR (I)

- NYU: image analogies (*SIGGRAPH 2001*)
  - Training pairs



EX: Learning-based SR (II)

EX: Learning-based SR (III)

- NYU: image analogies (*SIGGRAPH 2001*)
  - Training pairs

EX: Learning-based SR (IV)

EX: Learning-based SR (VI)

- Liu & Shum (CVPR-01)
  - Two-step approach to hallucinating faces
  - Global parametric model
    - Global face image by PCA
  - Local nonparametric model
    - Patch-based MRF network

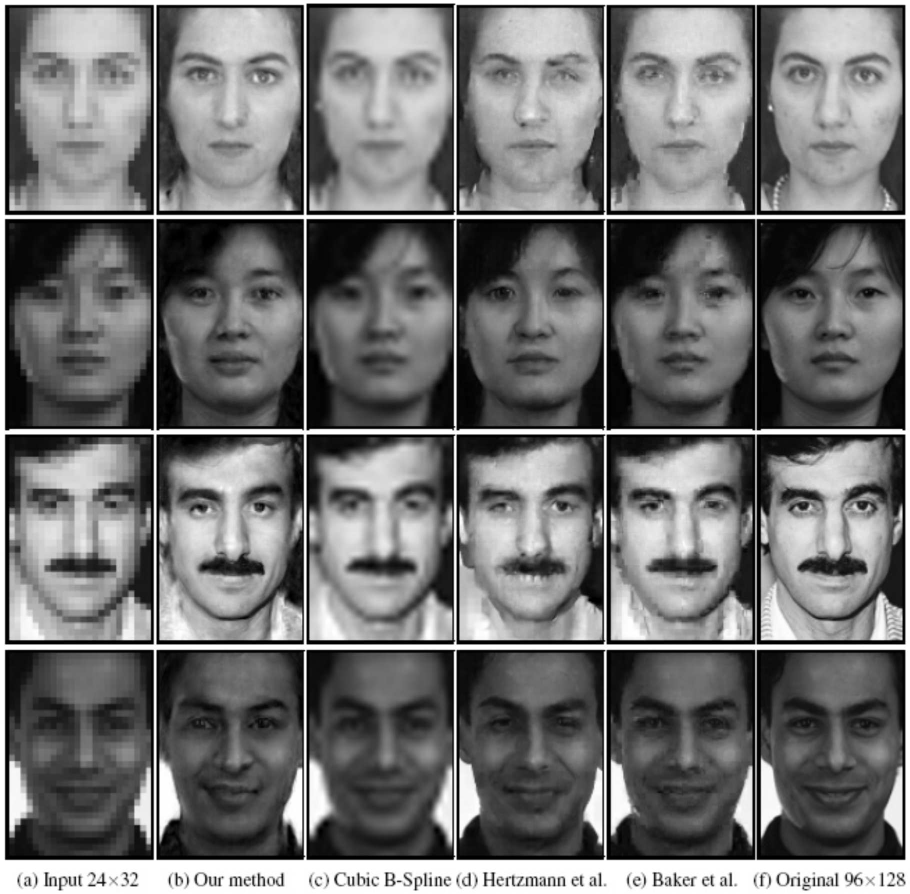
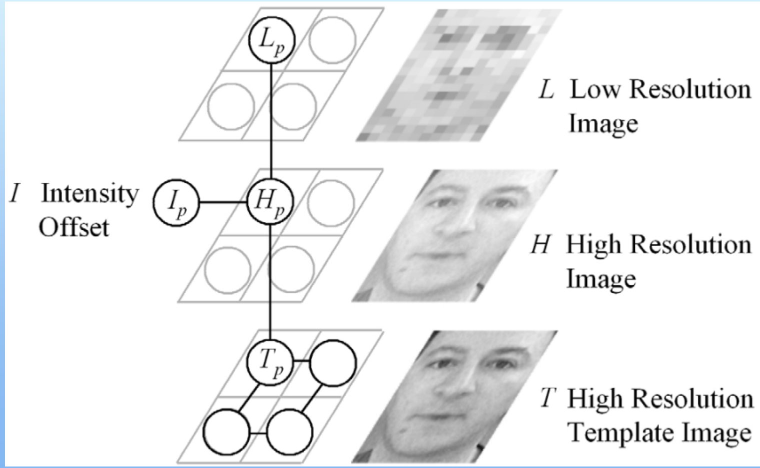
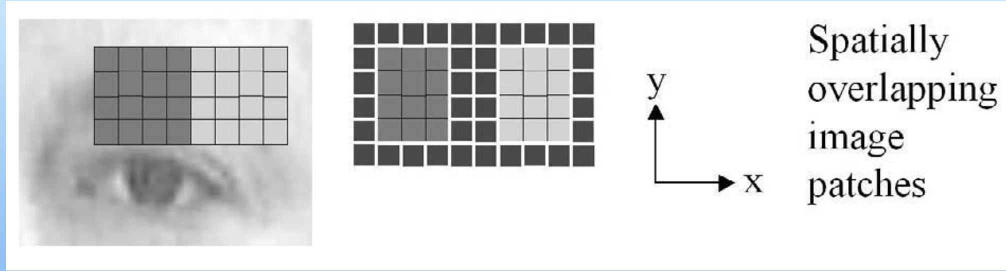


Figure 5. Comparison between our method and others.

Learning-based SR (I)

- Hallucinating faces in video
  - G. Dedeogle, T. Kanade, J. August, “High zoom video hallucination by exploiting spatio-temporal regularities”, CVPR-2004.
  - MRF models of HD images
    - Using spatial-temporal correlations in video frames
    - Overlapped blocks, intensity





Learning-based SR (II)

- Problem statement

$$(H_{MAP},\ I_{MAP}) \triangleq \arg\max_{H,I}\ logP(H,\ I \mid L).$$

- Marginalization over Template T

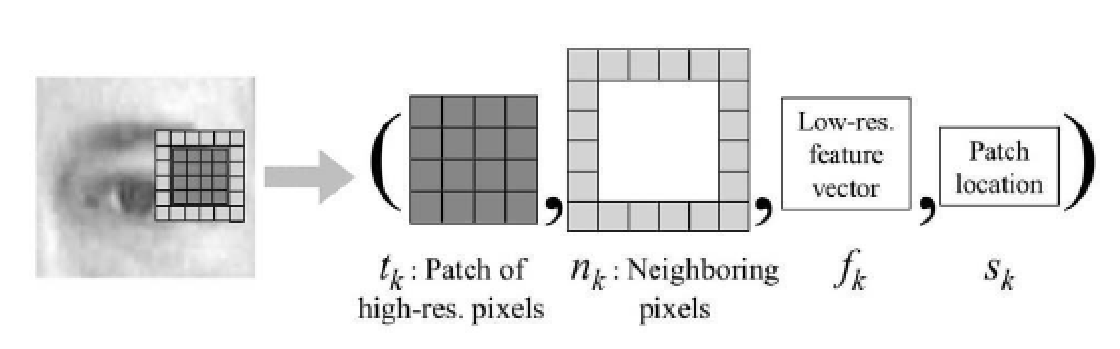
$$P(H,\ I \mid L) = \sum_T P(H, I, T \mid L)$$

- Bayesian Rule

$$\begin{aligned} & \sum_T \left\{P(H \mid I, T, L)\ P(I, T \mid L)\right\} \\ = & \sum_T \left\{P(H \mid I, T, L)\ P(I \mid T, L)\ P(T \mid L)\right\}. \end{aligned}$$

Learning-based SR (III)

- Data Entry for energy function



- Likelihood model

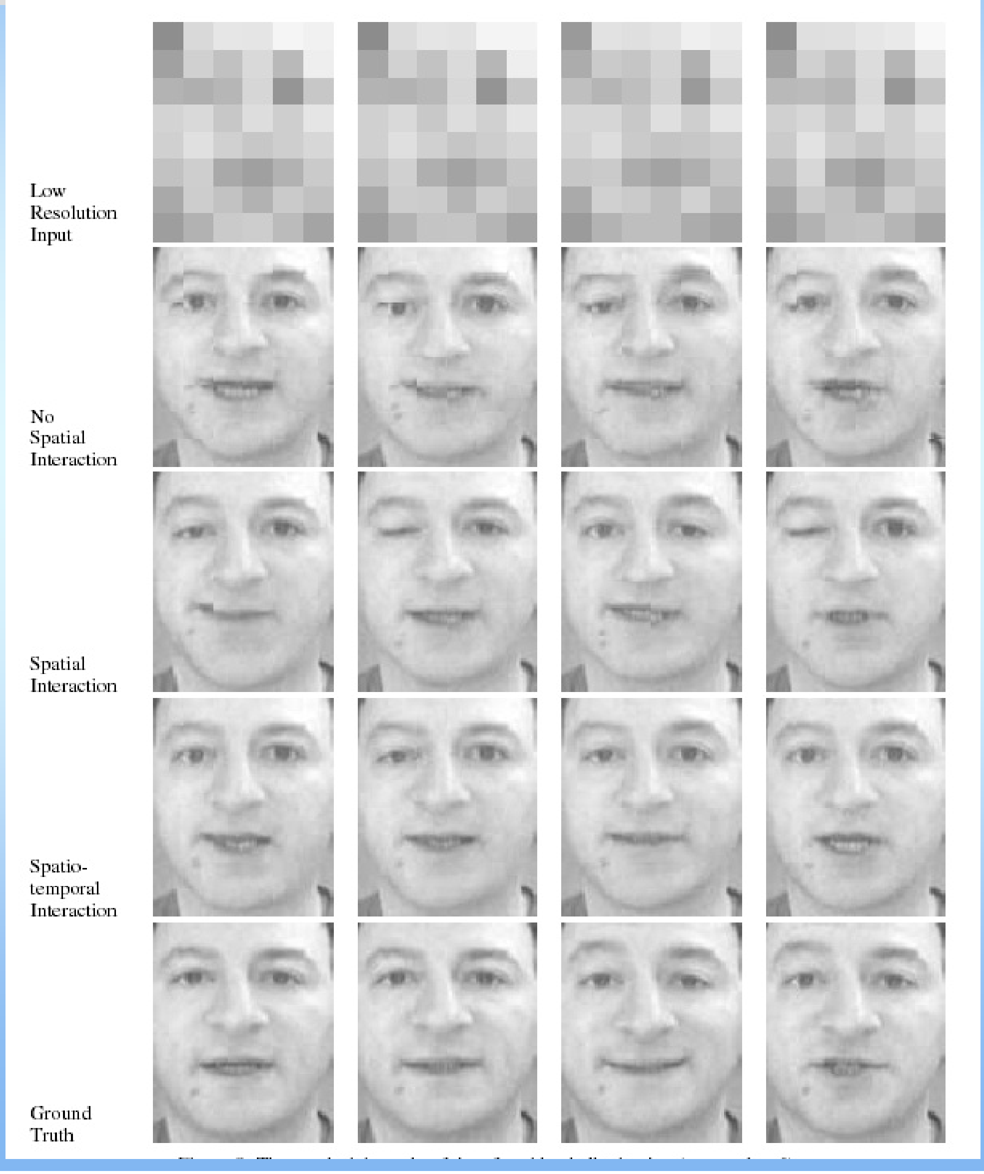
$$P(L \mid H)=\prod_{l=1}^{N} \frac{1}{\sigma_L \sqrt{2\pi}} \, exp\Big(- \frac{\big(L(l)-(AH)(l)\big)^2}{2\,\sigma_L{}^2}\Big).$$

- Prior model

$$\phi(T_p = t_k, T_q = t_l) \propto exp\Big(- \sum_{overlap} \big(t_k(u) - n_l(v)\big)^2 - \sum_{overlap} \big(n_k(u) - t_l(v)\big)^2 \Big)$$

Learning-based SR (IV)

- 결과
  - 8배 확대



Learning-based SR (V)

- Single image SR
  - D. Glasner “Super resolution from a single image, ”2009 CVPR
  - Finding and using similar patterns in the various scales of an image

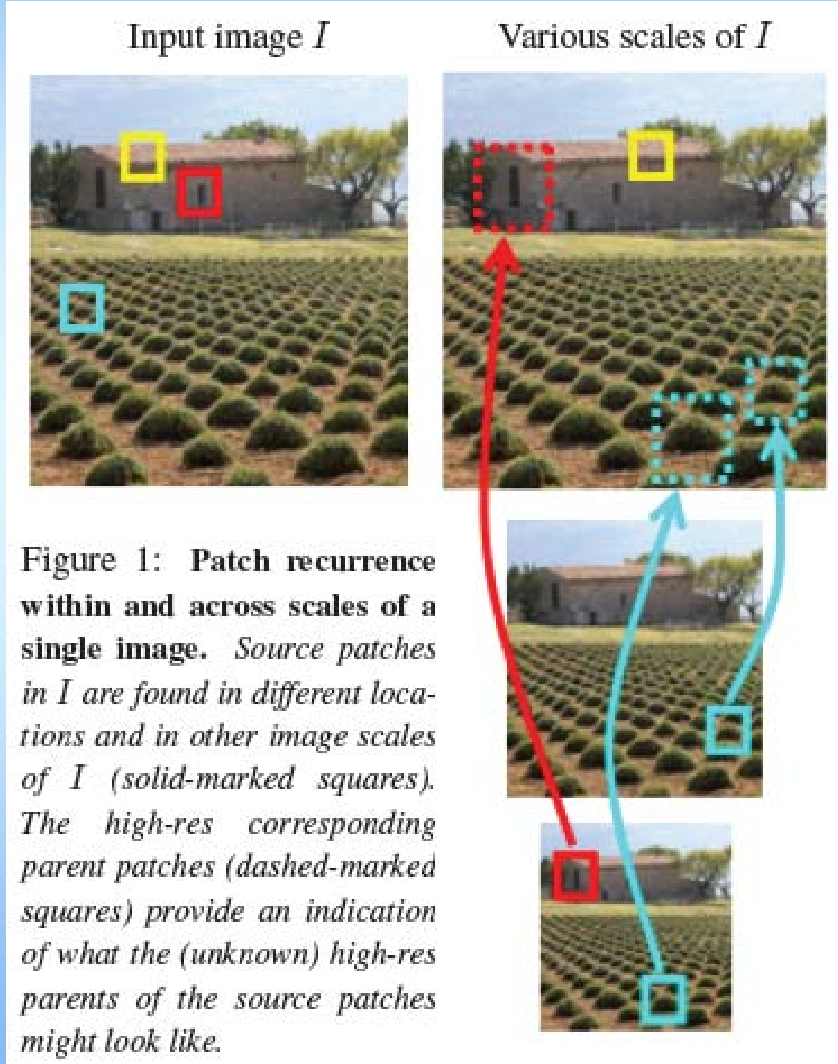


Figure 1: **Patch recurrence within and across scales of a single image.** *Source patches in I are found in different locations and in other image scales of I (solid-marked squares). The high-res corresponding parent patches (dashed-marked squares) provide an indication of what the (unknown) high-res parents of the source patches might look like.*

Learning-based SR (VI)

- Results of Single image SR

(a) Input image (scaled for display). (b) Bicubic interpolation (×2). (c) Within image repetitions (×2). (d) Unified single-image SR (×2).

(a) Input. (b) Bicubic interpolation (×3). (c) Unified single-image SR (×3). (d) Ground truth image.

Applications of SR

- Satellite Imaging
- Remote Sensing
- Video Surveillance (Face Recognition)
- Video Enhancement and Restoration
- Medical Imaging (CT, MRI, Ultrasound)
- DeMosaic
- Low Bit Rate video transmission
- Video encryption