Super-Resolution Imaging

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Resolution

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- Resolution: Smallest measurable detail in a visual presentation
- Spatial Resolution: spacing of pixels in an image measured in pixels per inch (ppi)
- High Spatial Resolution: Pixel density is high. (Larger no of pixels in an image)

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- HR Applications : Medical Imaging, Satellite imaging, remote sensing etc

Problem

- Super-Resolution (SR): Obtain high resolution from several low resolution observations of the same scene. (minimizes aliasing and blurring).

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- Why SR ?
  1. Cost 2. Shot noise
- Conventional Interpolation Methods : Nearest Neighbor or zero order hold or pixel replica, Bilinear, Bicubic
- Disadvantage : Single image used. Do not consider the aliasing or blurring.

The Idea!

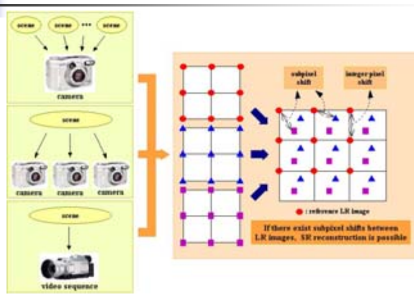
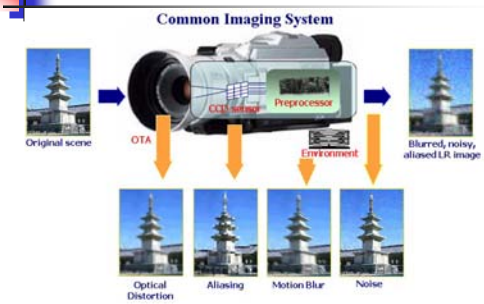
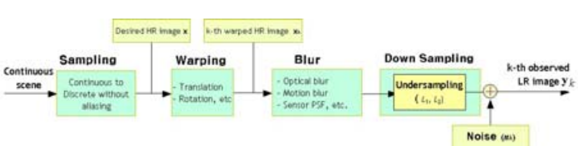


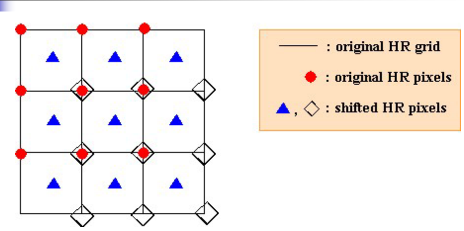
Illustration of Effects



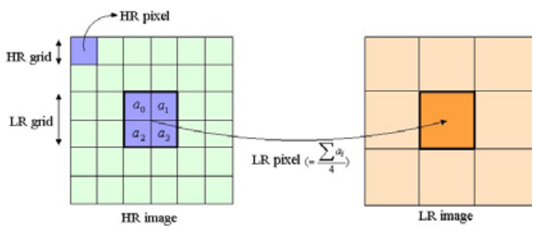
SR Model



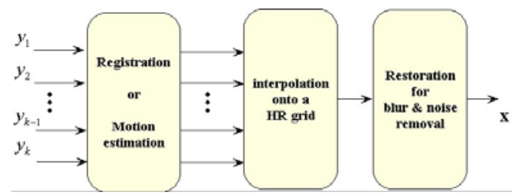
Illustration



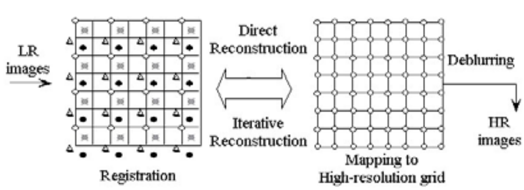
HR → LR Transformation



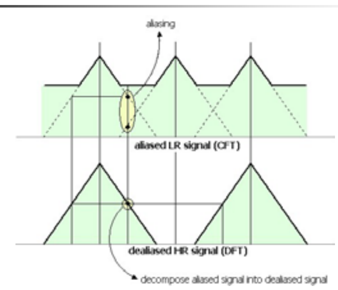
SR Restoration



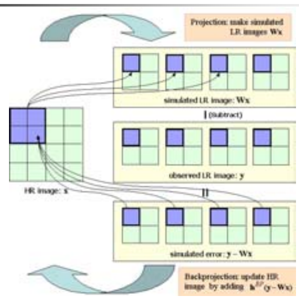
LR → HR Transformation



Aliasing Example



HR Restoration



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Different types of Cues to Solve Super-resolution Problem

- Motion
- Blur
- Zoom
- Photometry
- Learning based techniques

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SR USING ZOOM CUE

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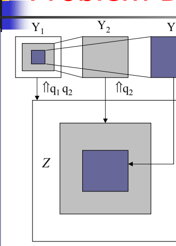
Problem Definition



Y_1 : Least zoomed image

Y_3 : Most zoomed image

q : Zoom factor

Problem : Given $Y_1, Y_2, \ldots, Y_p$ (Y_p has highest resolution), obtain the resolution of Y_1 at resolution of Y_p

Assumption made : Zoom factors are known.

noise is i.i.d gaussian

Motivation

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- An application of SR.
- Uses zoom as a cue.
- Resolution enhancement in remote sensing data.

Model for low resolution image

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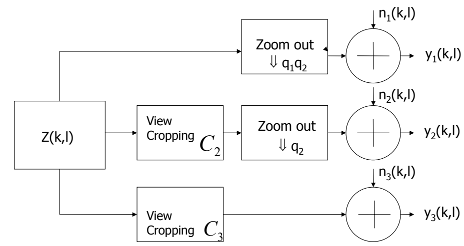
Observation model : $\underline{y}_m = D_m C_m (\underline{z} - \underline{z}_m) + \underline{n}_m \qquad m = 1.....p$



Solution

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- Use MAP a maximum *a posteriori* estimation

$$\hat{z} = \arg\max \; p(\underline{z} / \underline{y}_1, \underline{y}_2, ..., \underline{y}_p)$$

- Assume $\underline{z}$ to be an MRF (Markov Random field)
- Cost to be minimized

$$\varepsilon = \lambda \sum_{m=1}^{p} \| \underline{y}_m - D_m C_m (\underline{z} - \underline{z}_m) \|^2 + \sum_{c \in C} V_c(\underline{z})$$

Markov Random Field (MRF)

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- Models the a priori probability of context dependent entities : image pixels, depth etc.
- Regularizes the solution.
- Reconstruction smooth.
- Include line fields.

Experimental Results

Observed images of Nidhi captured with 3 different zoom settings.

Zoomed Nidhi image formed by using successive zero-order hold expansion.

Super-Resolved Nidhi image.

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Experimental Results (contd.)

Observed images of a house captured with 3 different zoom settings.

Zoomed house image formed by using successive zero-order hold expansion.

Super-Resolved house image.

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Experiments with Zoom Estimation

(a) (b) (c)

Observed images of Nidhi captured captured with three different Unknown zoom settings.

Zoom factor = 1.72 Estimated

Image obtained by aligning (b) and (c)

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SR with estimated zoom

Zoomed Nidhi image formed by using successive Bicubic expansion.

Super-resolved image

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LEARNING OF PRIORS FROM ZOOMED OBSERVATIONS

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SR with MRF Parameters Estimation

- Based on Maximum likelihood estimation

$$\hat{\theta} = \arg\max_{\theta} P(Z = \mathbf{z} | \theta)$$

$\theta = [\beta_1, \beta_2]^T$ for first order neighborhood

$\theta = [\beta_1, \beta_2, \beta_3, \beta_4]^T$ for second order neighborhood

Assumption made : Entire scene is statistically homogeneous

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SR with SAR (Simultaneous auto regressive) parameters estimation

Model:

$$z(s) = \sum_{r \varepsilon D} \theta(r) z(s+r) + w(s)$$

Where D is the set of neighbors of pixel at site s
$w(.)$ is i. i. d noise sequence with zero mean and variance σ^2

$$\theta(r) = \theta(-r)$$

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Experiments with MRF parameters Estimation

Observed images of texture with three different zoom settings

MRF parameters learnt from most zoomed observation using Maximum pseudolikelihood (MPL) estimation Yu and Cheng PRL,2003

SR with MRF Parameters estimated (cont.)

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Bilinear Interpolation

Proposed Approach

SR with SAR Parameters estimated

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Super-resolved image

SAR parameters learnt from most zoomed observation using maximum likelihood (ML) criterion Kashyap and Chellappa IEEE IT, 1983

An Experiment with a zoom factor of 2

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Observed images of a texture with two different zoom settings

Experiments with MRF and SAR parameters Estimation

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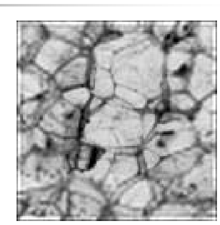
Bilinear Interpolation



Proposed MRF based Approach

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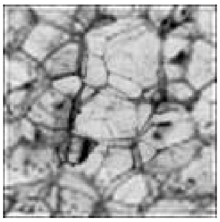

Proposed SAR based Approach

Experiments with parameters Estimation (contd.)

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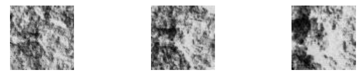

Observed images of texture with three different zoom settings

SR with MRF Parameters Estimated

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Bilinear Interpolation

Proposed Approach

Experiment with SAR parameters Estimation

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Super-resolved image

Experiments with parameters Estimation (contd.)

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Observed images of flower captured with three different unknown zoom settings .

SR with MRF Parameters Estimated

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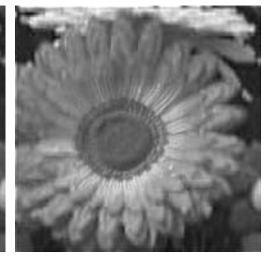
Bilinear interpolation



Super-resolved image

Conclusion

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- The super-resolved image is modeled as MRF or as an SAR and an MAP estimate and regularization based approach are used to solve the problem.
- Reconstruction not very good at zoomed out portions as expected.

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SR IMAGE AND STRUCTURE: USE OF PHOTOMETRIC CUE

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- Problem Definition: Given the photometric measurements obtain the super-resolved image as well as dense depth map.

Advantage:

- No need for image registration.
- 3D shape preservation is used as constraint.

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- Model Used:

$$y_m = F_{C_m}(D, z, R) + n_m, \qquad m = 1, \cdots, p$$

- Assumptions made :
  - Light Source directions are known
  - Reflectance model is known

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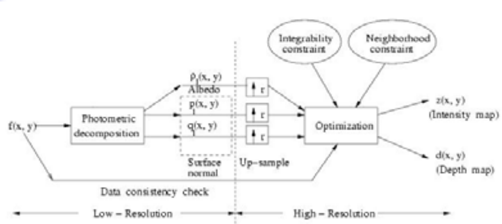
Illustration of SR using Photometric Cue



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Regularization

1. MRF-based Approach
   - Using Photometric Stereo
     $z = \rho(x \uparrow r, y \uparrow r)\hat{n}(x \uparrow r, y \uparrow r).\hat{s}$
   - p, q, and albedo are modeled as separate MRF's
   - Integrability constraint imposed
   - Data consistency check included

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- Final cost minimized :

  ε = Reflectance model error
  \+ Integrability constraint
  \+ Smoothness priors
  \+ Data consistency error

$$\varepsilon = \| \underline{z} - \rho(x \uparrow r, y \uparrow r)\hat{n}(x \uparrow r, y \uparrow r).\hat{s} \|^2$$
$$+ \lambda \| (\underline{p}_y - \underline{q}_x)(1 - l_p)(1 - v_q) \|^2$$
$$+ U(\underline{z}) + U(\underline{p}) + U(\underline{q}) + U(\underline{\rho})$$
$$+ \alpha \| \underline{y} - HD\underline{z} \|^2$$

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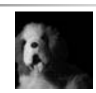
Experimental Results



An observed image of dog 'Jodu' with the light source position (-0.8389, -0.7193)

Bilinearly Interpolated Jodu

Super-resolved Jodu using generalized interpolation

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Experimental Results (contd.)

Super-resolved Jodu using the MRF-based approach

Super-resolved, synthesized view of Jodu for source position (0.0, 0.0) for which the observation is not captured.

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Experimental Results (contd.)

SR depth map of Jodu using the Generalized interpolation

SR depth map obtained using the MRF-based approach

Experimental Results (contd.)

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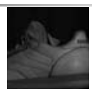

An observed shoe image captured with light source position (0.4663, 0.3523)

Super-resolved shoe image using generalized interpolation

Super-resolved shoe image using MRF-based approach

Experimental Results (contd.)

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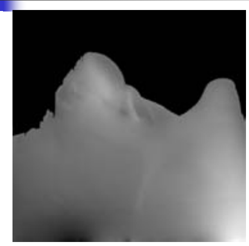
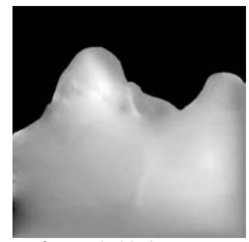


Super-resolved depth map of shoe image using the generalized interpolation



Super-resolved depth map using the MRF-based approach

2. Variational Approach Results

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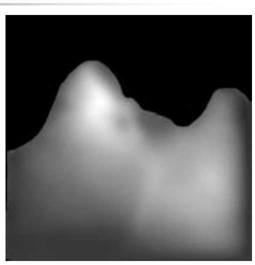
SR depth map of Jodu using the variational approach



SR depth map of shoe image using the variational approach

Conclusions

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- The super-resolved image z, surface gradients p, q and the albedo are modeled as separate MRFs and the regularization based technique is used to solve the problem.
- Problem also solved using variational approach where smoothness of the function is used as regularization term : Faster Computations.

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JOINT BLIND RESTORATION AND SURFACE RECOVERY IN PHOTOMETRIC STEREO

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- **Problem:** Simultaneous estimation of scene structure and restoration of images from blurred observations captured under different light source positions keeping both camera and object stationary.
- Model Used: $\underline{g}_m = H(\sigma)\underline{f}_m(p,q,\rho) + \underline{n}_m, \quad m = 1,\ldots,k$
- A restoration and shape recovery problem

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Solution

- Cost = model consistency term for p observations + smoothness terms

  minimize with respect to surface gradients and albedo.

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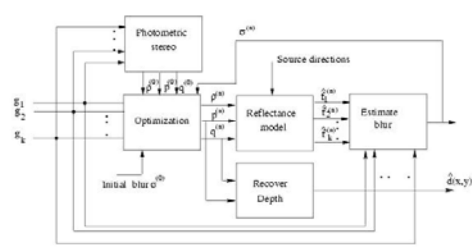
Illustration of Proposed Method (PSF Unknown)



Experimental Results (Known blur)

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Focused Jodu image for two different source positions

Experimental Results (cont.)

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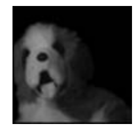

Blurred (pill-box) Jodu image for the same source positions

Experimental Results (cont.)

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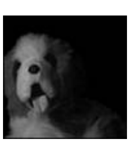
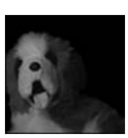

Estimated Jodu for the same source positions

Experimental Results (cont.)

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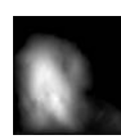
True depth map

Depth map due to blurred observations using photometric stereo



Estimated depth map using proposed approach

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Experimental Results (Unknown Blur)

Observed image of Jodu with an arbitrary camera defocus for a particular light source position

Restored Jodu using proposed approach

Blind Deconvolution

Estimated blur parameter = 1.0577

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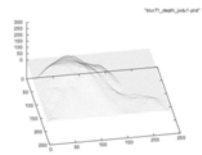
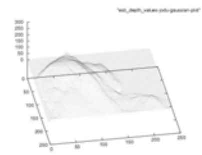
Experimental Results (cont.)



Recovered depth mesh plot using photometric stereo



Recovered depth using proposed approach

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Conclusions

- A blind restoration and structure recovery problem is addressed using photometric measurements.
- Results obtained show perceptual as well as quantifiable improvements over standard PS (photometric stereo), Lucy-Richardson algorithm for restoration and blind deconvolution.

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USE OF LEARNT WAVELET PRIOR

Problem Definition

- Given a low resolution image and a set of high resolution training images learn the high frequencies from the training data set and obtain SR.

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Approach

- Learn the wavelet coefficients at finer scales of the unknown high resolution image from high resolution training set.
- Final cost used for optimization: data fitting term + wavelet prior + smoothness prior

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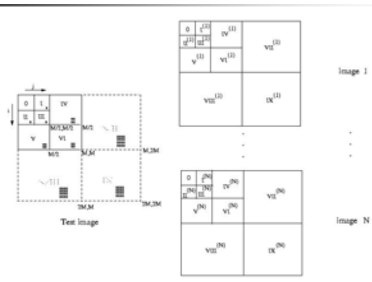
Learning:



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Experimental Results

Low resolution image

Bilinearly interpolated image

Super-resolved image

Experimental Results (cont.)

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Low resolution image

Bilinear interpolation

Super-resolved image

Conclusions

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- A learning based technique for super-resolution using a single low resolution image is described.
- Learning represents the next challenging frontier for computer vision.