

Image Restoration with Union of Directional Orthonormal DWTs

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1 Introduction

- Image Restoration with Sparse Representation
- Selection of Dictionary
- Purpose

2 Union of Directional SOWTs

- Review of 2-D Directional LOT
- Construction of Redundant Dictionary

3 Image Restoration with ISTA

- ISTA with a Tight Frame
- Examples of Measurement Processes

4 Simulation Results

- Original Pictures and Adopted Transforms
- Deblurring, Super Resolution and Inpainting

5 Conclusions

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Image Restoration with Sparse Representation

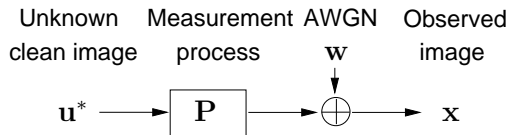


Image Restoration with Sparse Representation

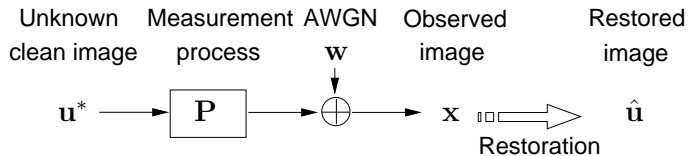


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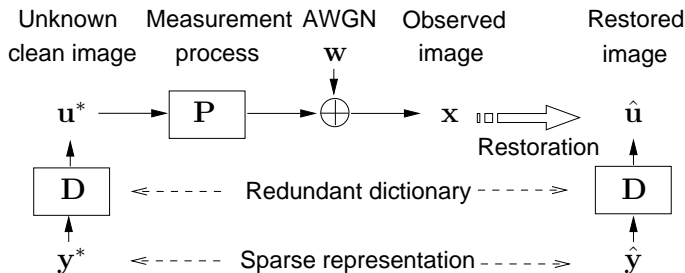
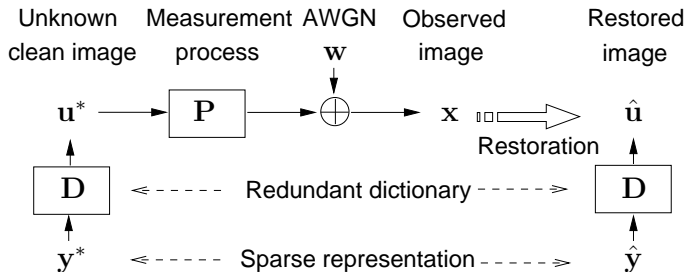


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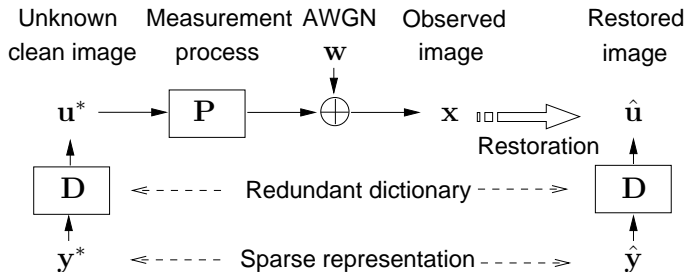


Assumption

$$x = Pu^* + w$$

$$u^* = Dy^*$$

Image Restoration with Sparse Representation



Assumption

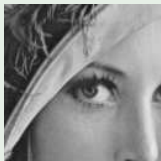
$$\mathbf{x} = \mathbf{P}\mathbf{u}^* + \mathbf{w}$$
$$\mathbf{u}^* = \mathbf{D}\mathbf{y}^*$$

Example of Problem Setting

$$(Q_1^\lambda) \quad \hat{\mathbf{y}} = \arg \min_{\mathbf{y}} \|\mathbf{x} - \mathbf{P}\mathbf{D}\mathbf{y}\|_2^2 + \lambda \|\mathbf{y}\|_1$$
$$\hat{\mathbf{u}} = \mathbf{D}\hat{\mathbf{y}}$$

Selection of Dictionary

Selection of an appropriate dictionary is a KEY STEP in (Q_1^λ).



Original

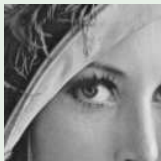


Observed

ISTA: Iterative Shrinkage/Thresholding Algorithm

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Original



Observed

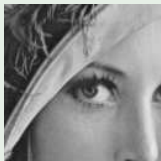


NS-Haar WT

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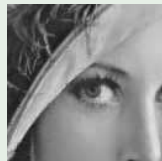
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NS-Haar WT



Proposal

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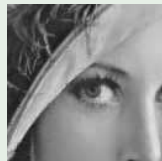
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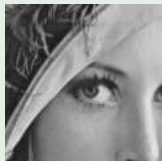
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What kind of properties are preferable?

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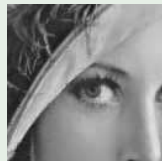
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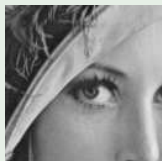
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- Redundant (sparse representation)

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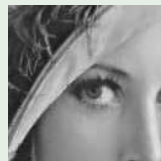
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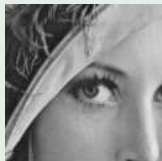
What kind of properties are preferable?

- Redundant (sparse representation)
- Overlapping (smoothness)

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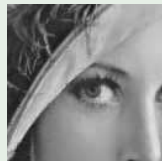
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Proposal

What kind of properties are preferable?

- Redundant (sparse representation)
- Overlapping (smoothness)
- Symmetric (anti-phase-distortion)

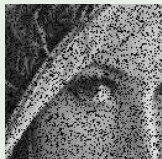
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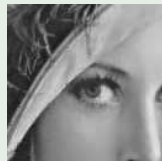
Original



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Proposal

What kind of properties are preferable?

- Redundant (sparse representation)
- Overlapping (smoothness)
- Symmetric (anti-phase-distortion)
- Tight (energy preservation)

ISTA: Iterative Shrinkage/Thresholding Algorithm

Selection of Dictionary

As well, the DIRECTIONAL property is of interest.

Good approximation for diagonal edges and textures.

Real-valued and compact-support dictionaries

| Dictionaries | Dir. | Red. | Ovl. | Sym. | Tight |
|-------------------|------|------|------|------------|-------|
| DCT | No | No | No | Yes | Yes |
| Haar DWT | No | No | No | Yes | Yes |
| 5-3/9-7 DWT | No | No | Yes | Yes | No |
| NS-DCT | No | Yes | Yes | Yes | Yes |
| NS-Haar DWT | No | Yes | Yes | Yes | Yes |
| DirSOWT | Yes | No | Yes | Yes | Yes |
| Contourlet | Yes | Yes | Yes | Restricted | |
| Union of DirSOWTs | Yes | Yes | Yes | Yes | Yes |

Contourlet: [Do et al., IEEE TIP 2005]

DirSOWT: [Muramatsu et al., IEEE TIP 2012]

- A union of DirSOWTs was applied to image denoising as a redundant dictionary \mathbf{D} and shown to be effective.

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Extend the application of a union of DirSOWTs to image restoration.

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Review of 2-D Directional LOT

- A DirSOWT, directional symmetric orthonormal WT, is a hierarchical tree construction of a directional LOT (DirLOT).

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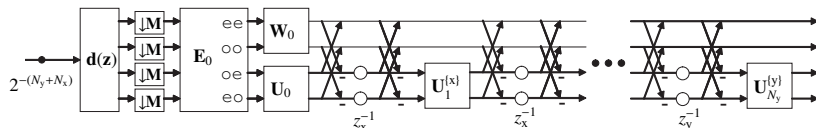
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 - Capable to hold trend vanishing moments (TVMs)
- Constructed by a lattice structure



- $\mathbf{d}(\mathbf{z})$ is a 2-D delay chain.
- \mathbf{E}_0 is a symmetric orthonormal matrix given by the 2-D DCT.
- \mathbf{W}_0 , \mathbf{U}_0 and $\mathbf{U}_{n_d}^{(d)}$ are parameter orthonormal matrices.

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Construction of Redundant Dictionary

Examples of 2×2 -decomposition NS GenLOT/DirLOT bases



Iterative decomposition
yields SOWT



$$\mathbf{D} = \left[\Phi_{0 \cup \frac{\pi}{2}}^T \quad \Phi_{\phi_1}^T \quad \Phi_{\phi_2}^T \quad \Phi_{\phi_3}^T \quad \dots \quad \Phi_{\phi_{K-1}}^T \right]$$

- $\Phi_{0 \cup \frac{\pi}{2}}$ is a nondirectional SOWT with the classical two-order VMs.
- Φ_{ϕ} is a DirSOWT with the two-order TVMs for the direction $\mathbf{u}_{\phi} = (\sin \phi, \cos \phi)^T$.

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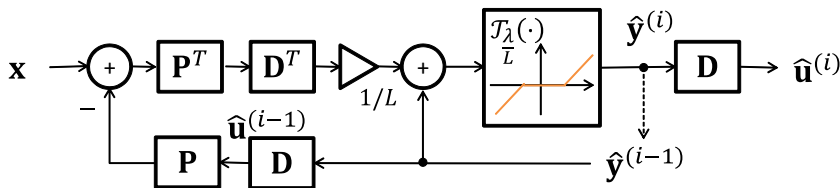
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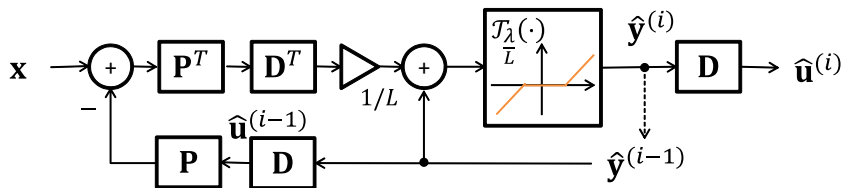
ISTA with a Tight Frame

- ISTA solves (Q_1^λ) exactly.



ISTA with a Tight Frame

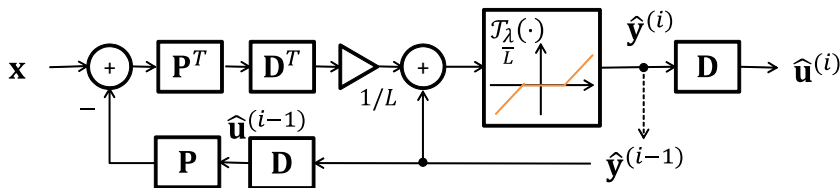
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- If \mathbf{D} is a tight frame and $\mathbf{D}\mathbf{D}^T = K\mathbf{I}$
 $\Rightarrow L = K\lambda_{\max}(\mathbf{D}^T\mathbf{P}^T\mathbf{P}\mathbf{D}) = K\lambda_{\max}(\mathbf{P}^T\mathbf{P})$

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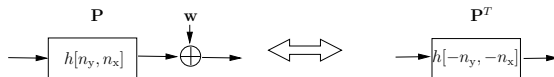


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 $\Rightarrow L = K\lambda_{\max}(\mathbf{D}^T\mathbf{P}^T\mathbf{P}\mathbf{D}) = K\lambda_{\max}(\mathbf{P}^T\mathbf{P})$
- Linear measurement process \mathbf{P} is pluggable and applicable to
 - Deblurring
 - Super resolution
 - Inpainting and so on

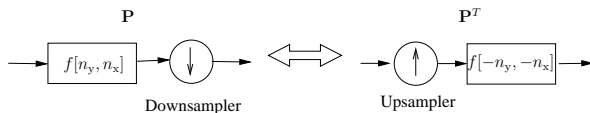
Examples of Measurement Processes

Relation between measurement process and its adjoint

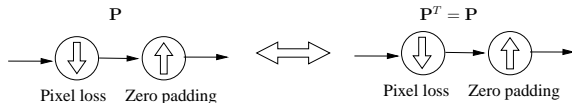
- Deblurring



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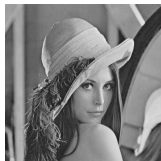
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Original Pictures and Adopted Transforms



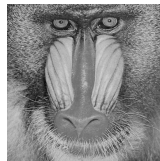
goldhill



lena



barbara



baboon

Original pictures \mathbf{u}^* of size 512×512 , 8-bit grayscale.

Adopted dictionaries

| Abrv. | Features |
|-------|--|
| NSHT | Two-level non-subsampled Haar DWT, separable, tight, nondirectional |
| UDN4 | Union of six-level SOWT and DirSOWTs with two TVMs of $[N_y, N_x]^T = [4, 4]^T$, non separable, tight, multidirectional |



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Simulation Results in SSIM - Deblurring



Observed



Wiener



NSHT($K = 7$)

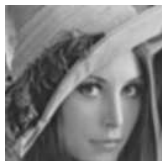


UDN4($K = 5$)

Partial results of deblurring for “lena.”

| Picture | Wiener | NSHT(λ) | UDN4(λ) |
|-----------------|--------|-----------------------|-----------------------|
| <i>goldhill</i> | 0.633 | 0.720 (0.0007) | 0.724 (0.0026) |
| <i>lena</i> | 0.666 | 0.796 (0.0006) | 0.820 (0.0054) |
| <i>barbara</i> | 0.543 | 0.654 (0.0007) | 0.667 (0.0043) |
| <i>baboon</i> | 0.517 | 0.529 (0.0005) | 0.528 (0.0000) |

Simulation Results in SSIM - Super Resolution



Observed



Bicubic



NSHT($K = 7$)



UDN4($K = 5$)

Partial results of super resolution for “lena.”

| Picture | Bicubic | NSHT(λ) | UDN4(λ) |
|-----------------|--------------------|-----------------------|-------------------|
| <i>goldhill</i> | 0.682 ¹ | 0.767 (0.0003) | 0.759 (0.0004) |
| <i>lena</i> | 0.802 | 0.859 (0.0003) | 0.854 (0.0004) |
| <i>barbara</i> | 0.646 | 0.701 (0.0004) | 0.696 (0.0004) |
| <i>baboon</i> | 0.433 | 0.551 (0.0002) | 0.544 (0.0003) |

¹Wrongly typed in the proceedings



Simulation Results in SSIM - Inpainting



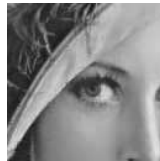
Observed



Median



NSHT($K = 7$)



UDN4($K = 5$)

Partial results of inpainting for “lena.”

| Picture | Median | NSHT(λ) | UDN4(λ) |
|-----------------|--------|-------------------|-----------------------|
| <i>goldhill</i> | 0.632 | 0.609 (0.0318) | 0.931 (0.0197) |
| <i>lena</i> | 0.655 | 0.560 (0.0385) | 0.945 (0.0206) |
| <i>barbara</i> | 0.602 | 0.647 (0.0300) | 0.944 (0.0220) |
| <i>baboon</i> | 0.522 | 0.638 (0.0324) | 0.907 (0.0251) |

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- A novel image restoration technique was proposed by introducing a union of DirSOWTs.
- The significance is verified through the application to
 - Deblurring
 - Super resolution and
 - Inpainting
- The proposed dictionary is shown to be superior to or comparable with the non-subsampled Haar WT.

Thank you very much for your attention!

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