FYP Presentation

IMAGE DEBLURRING

Image Upsampling via Tight Frames

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- Introduction

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- Tight frames

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- Multi-resolution analysis

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- Proposed Algorithm

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- Results

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- Proposed Algorithm
- Results
- Conclusion and future directions

Single Image Upsampling

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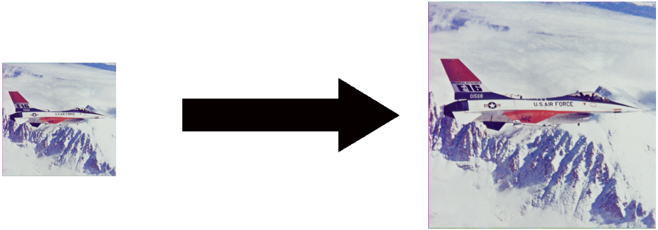

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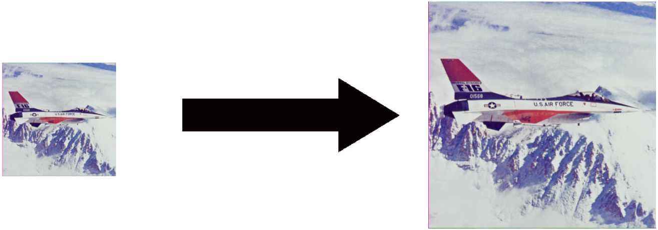

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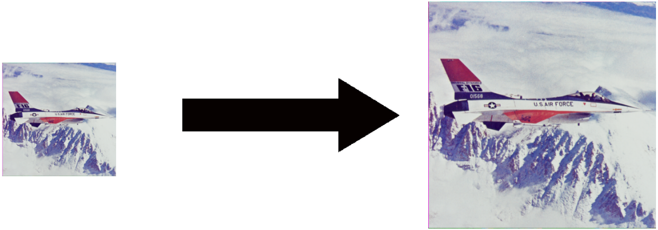

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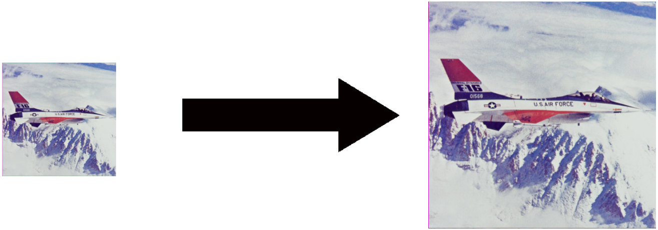

- Given an input image $\mathbf{f}_{input}$,
- let say, of 256 x 256 pixels;
- Reconstruct a 512 x 512 pixels image $\mathbf{f}_{desired}$.

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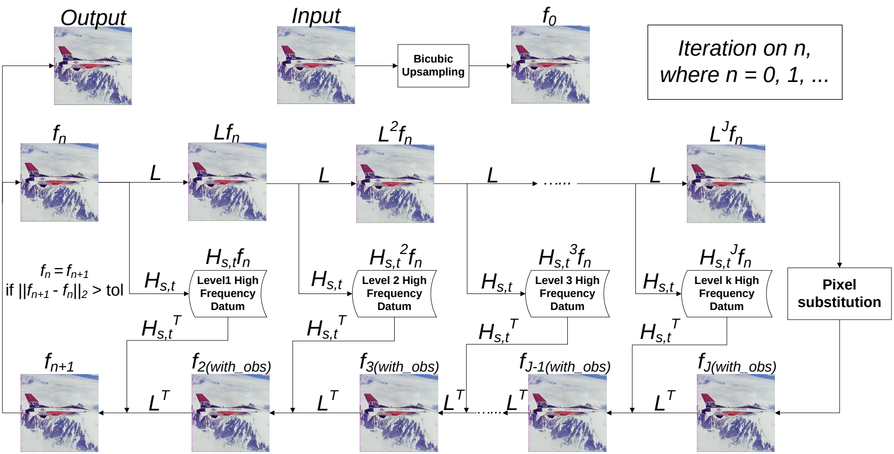
- Tight Frame and Multi-resolution Analysis
- to design our upsampling algorithm.

Our Proposed Algorithm



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- In addition, 2-D images are stacked column by column as a 1-D column vector in our algorithm.

Tight Frames

Tight Frames

A system X is called a *tight frames system* of $L_2(\mathbb{R})$ if

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A tight frames system can be constructed by starting with a scaling function $\phi \in L_2(\mathbb{R})$ and letting it satisfies the dilation equation:

$$\phi(x) = \sum_{n=-l_1}^{l_2} \sqrt{2} h_\phi(n) \phi(2x - n) \qquad \forall x \in \mathbb{R}. \tag{1}$$

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With this ϕ and given corresponding high-pass filters h_ψ with length $(s_2 - s_1)$,

one can find the tight frames function ψ by satisfying a similar dilation equation

$$\psi(x) = \sum_{n=-s_1}^{s_2} \sqrt{2} h_\psi(n) \phi(2x - n) \quad \forall x \in \mathbb{R}. \qquad (2)$$

Hence, given suitable low-pass and high-pass filters, one can construct a tight frames system

$$X_\Psi := \left\{ 2^{k/2}\psi(2^k x - j) \mid \psi \in \Psi; k, j \in \mathbb{Z} \right\}.$$

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- low-pass: $h_0 = \frac{1}{4}[1, 2, 1]$;
- high-pass: $h_1 = \frac{\sqrt{2}}{4}[1, 0, -1]$ and $h_2 = \frac{1}{4}[-1, 2, -1]$.

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e.g. H_0 for h_0 and $H_{0,0}$ for $h_{0,0}$ are written as

$$H_0 = \frac{1}{4}\begin{bmatrix} 2 & 1 & 0 & \cdots & 0 & 1 \\ 1 & 2 & 1 & \ddots & 0 & 0 \\ 0 & 1 & 2 & \ddots & 0 & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & \ddots & 2 & 1 \\ 1 & 0 & 0 & \cdots & 1 & 2 \end{bmatrix} \quad \text{and} \quad H_{0,0} = H_0^T \otimes H_0.$$

Then, we have this perfect reconstruction identity:

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Our algorithm is basically designed by using (3).

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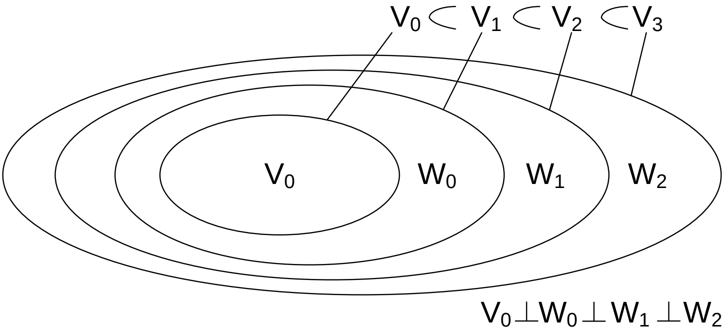
It can be illustrated by this graph:



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- By multi-resolution analysis,

$$V_J = W_J \oplus W_{J-1} \oplus \cdots \oplus W_0 \oplus V_0.$$

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$$\begin{aligned}\mathbf{f}_{desired} &= \sum_{s,t=0}^{2} H_{s,t}^T H_{s,t}\mathbf{f}_{desired} \\ &= H_{0,0}^T H_{0,0}\mathbf{f}_{desired} + \sum_{\substack{s,t=0 \\ (s,t)\neq(0,0)}}^{2} H_{s,t}^T H_{s,t}\mathbf{f}_{desired}\end{aligned}$$

$$= \quad (H_{0,0}^T)^2 (H_{0,0})^2 \mathbf{f}_{desired} + \sum_{j=0}^{1} \sum_{\substack{s,t=0 \\ (s,t)\neq(0,0)}}^{2} (H_{0,0}^T)^j H_{s,t}^T H_{s,t} (H_{0,0})^j \mathbf{f}_{desired}$$

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And our proposed algorithm is iterating on this equation (4) as:

$$\mathbf{f}_{n+1} = (H_{0,0}^T)^J D_{0,0}^T \mathbf{f}_{input} + (H_{0,0}^T)^J \sum_{\substack{m,n=0 \\ (m,n)\neq(0,0)}}^{1} D_{m,n}^T D_{m,n} (H_{0,0})^J \mathbf{f}_{n}$$
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3. Find $\mathbf{f}_{n+1}$ by the equation (5)
4. Set $\mathbf{f}^* = \mathbf{f}_{n+1}$ if $\|\mathbf{f}_{n+1} - \mathbf{f}_n\|_2 \leq tol$, where $\mathbf{f}^*$ is our upsampled image; else set $\mathbf{f}_n = \mathbf{f}_{n+1}$ and repeat step 3 and 4.

Results

Results

- Click Here (Hyper Link)
- Local Files:

  ->

Bicubic

TF Level 1

Bicubic

TF Level 4

Bicubic

TF Level 7

[Shan, 2009]

TF Level 1

[Shan, 2009]

TF Level 4

[Shan, 2009]

TF Level 7

Figure:
By [Shan,2009], Level 1, Level 2 and Level 3 (Upper: From left to right)
Level 4, Level 5, Level 6 and Level 7 (Lower: From left to right)

Bicubic

TF Level 1

Bicubic

TF Level 4

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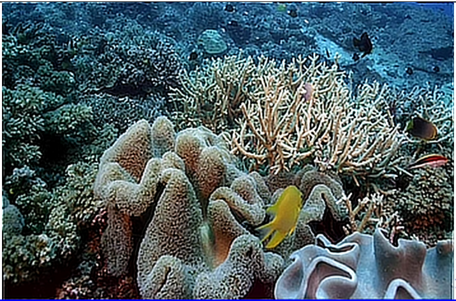
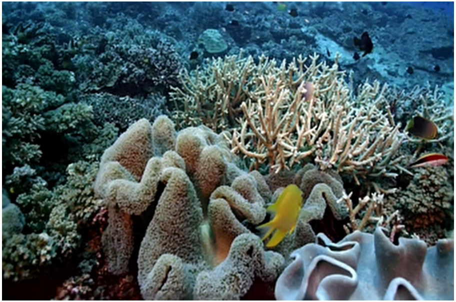
TF Level 7

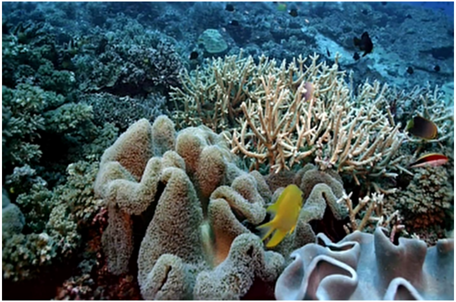


[Shan, 2009]



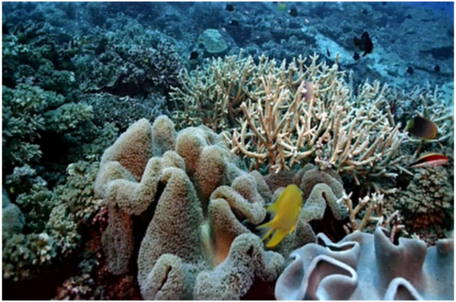
TE Level 1

[Shan, 2009]



TF Level 4

[Shan, 2009]



TF Level 7

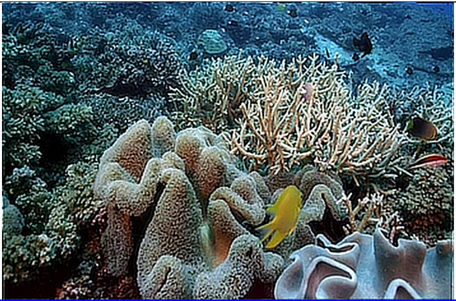


Figure:
By [Shan,2009], Level 1, Level 2 and Level 3 (Upper: From left to right)
Level 4, Level 5, Level 6 and Level 7 (Lower: From left to right)

Bicubic

TF Level 1

Bicubic

TF Level 4

Bicubic

TF Level 7

[Shan, 2009]

TF Level 1

[Shan, 2009]

TF Level 4

[Shan, 2009]

TF Level 7

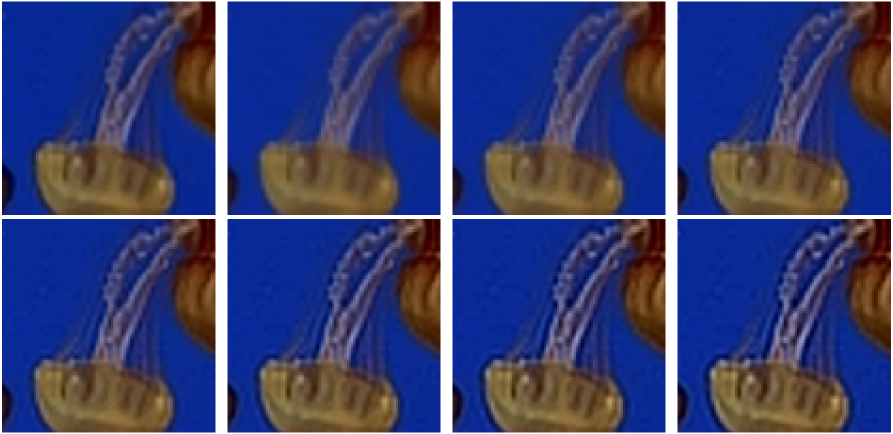


Figure:
By [Shan,2009], Level 1, Level 2 and Level 3 (Upper: From left to right)
Level 4, Level 5, Level 6 and Level 7 (Lower: From left to right)

Conclusions and Future Directions

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Time taken	79s	292s	10 mins	19 mins	36 mins	67 mins	112 mins

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Thanks for your attentions!

Q & A