

# MRA-based wavelet frames and digital Gabor filters

---

Zhao Yufei

Joint work with Ji Hui and Shen Zuowei

Department of Mathematics

National University of Singapore

May 2017

# Mathematical representation of images



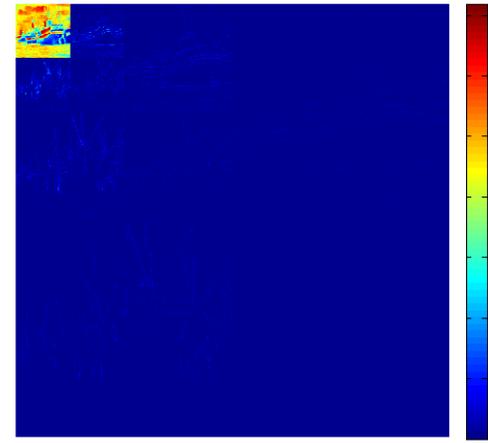
$\mathbf{f}$  : image



$$\mathbf{f} = \sum_{n \in I} c_n \mathbf{v}_n$$

$\{\mathbf{v}_n\}_{n \in I}$  : system

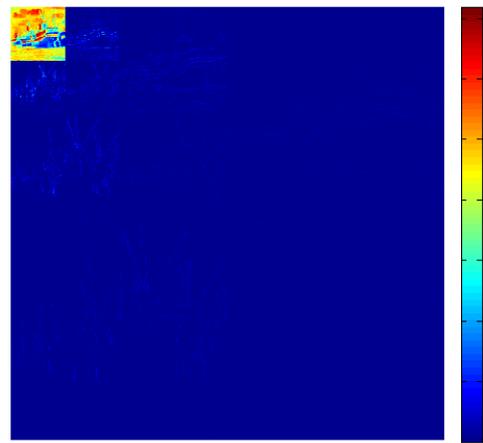
$\{c_n\}_{n \in I}$  : coefficients



# Mathematical representation of images



$$\mathbf{f} = \sum_{n \in I} c_n \mathbf{v}_n$$



$\mathbf{f}$  : image       $\{\mathbf{v}_n\}_{n \in I}$  : system       $\{c_n\}_{n \in I}$  : coefficients

A good system for image representation:

- ◆  $\{c_n\}$  has physical meanings.
- ◆  $\{c_n\}$  is sparse.
- ◆  $\{\mathbf{v}_n\}$  is an orthonormal basis or a tight frame.

$$\mathbf{f} = \sum_{n \in I} \langle \mathbf{f}, \mathbf{v}_n \rangle \mathbf{v}_n, \quad \forall \mathbf{f} \in \mathbb{C}^N$$

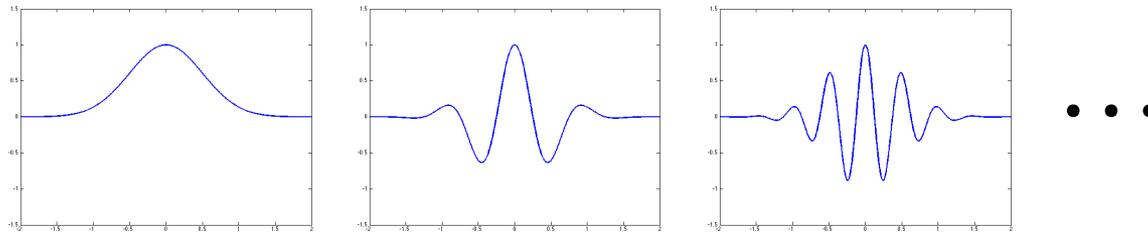
- ◆ Atoms  $\mathbf{v}_n$ 's are localized.

# Two kinds of widely used systems

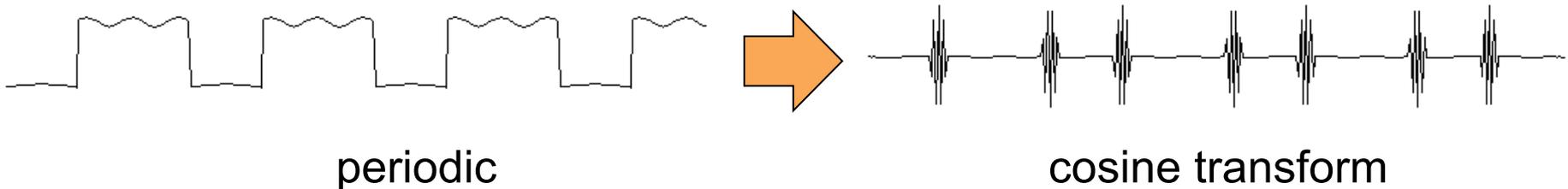
*Gabor or Cosine system* in  $L_2(\mathbb{R})$ :

$$\{g(t - ak)e^{2\pi i b t l}\}_{k, l \in \mathbb{Z}} \quad \text{or} \quad \{g(t - ak)\cos(\pi b l t)\}_{k, l \in \mathbb{Z}}$$

◆ **Example:**



◆ Provide accurate local time-frequency analysis



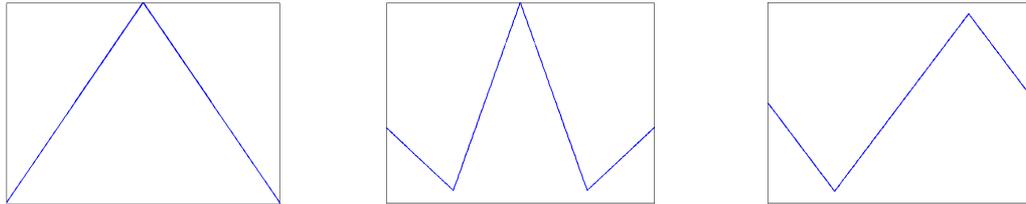
◆ Discretization of Gabor or Cosine systems: sampling the continuous atoms

◆ Drawback: lack of multi-scale property

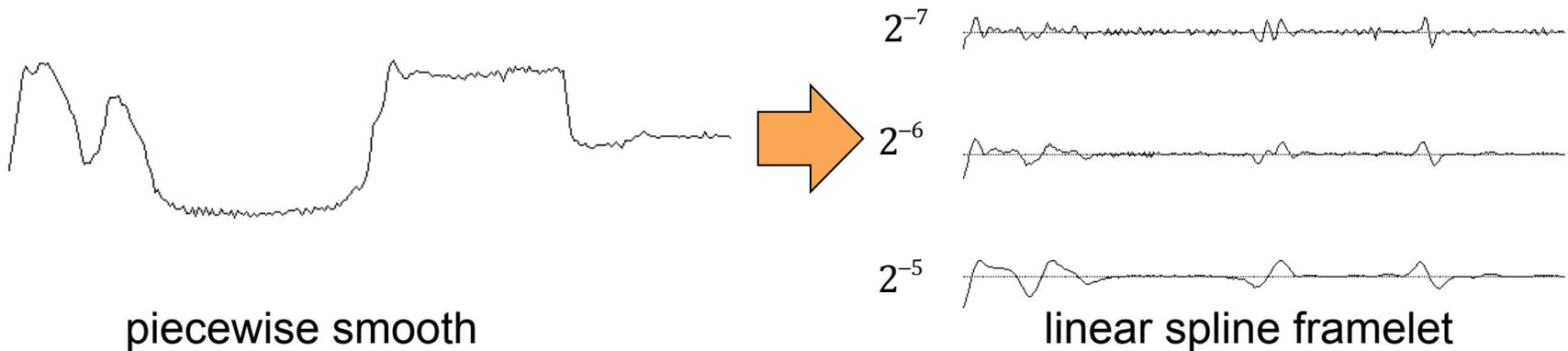
# Cont'd

*Wavelet system* in  $L_2(\mathbb{R})$ :  $\{2^{n/2}\psi_\ell(2^n t - k)\}_{n,k \in \mathbb{Z}, 1 \leq \ell \leq r}$

◆ **Example:** linear spline wavelet



◆ Providing local discontinuity measurements in multi-scales

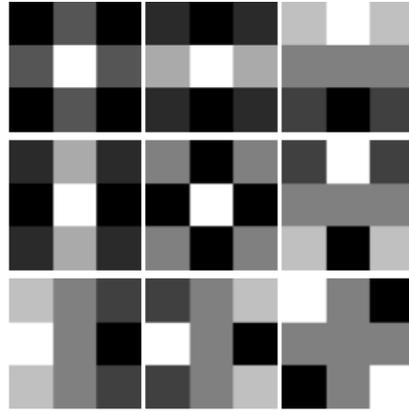


◆ Discrete wavelet systems are generated by the filter bank

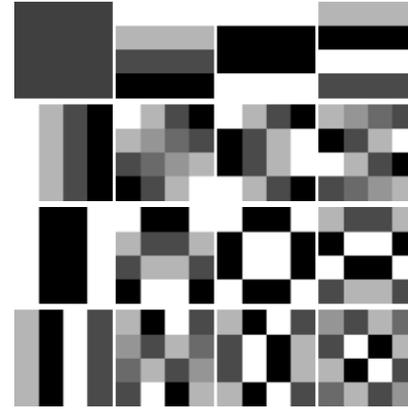
◆ Drawback: weak local time-frequency analysis

# 2D system: tensor product of 1D systems

- ◆ 2D filters (elementary atoms)



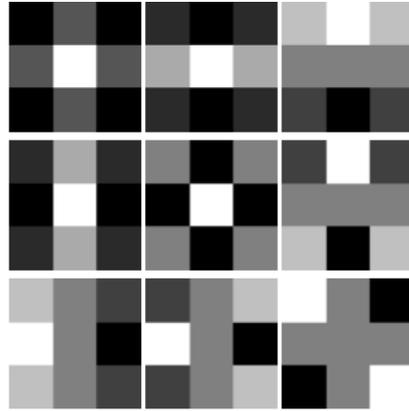
linear spline wavelet



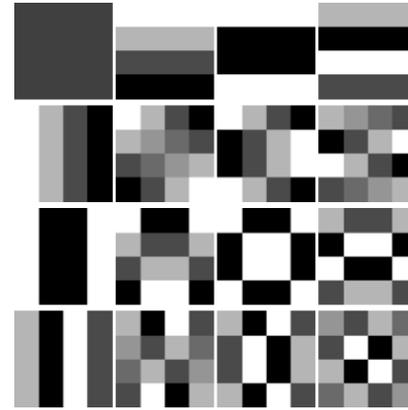
local DCT

# 2D system: tensor product of 1D systems

- ◆ 2D filters (elementary atoms)



linear spline wavelet

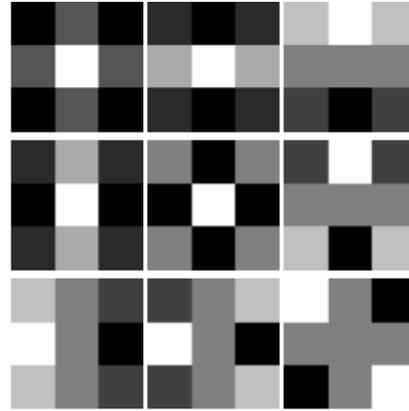


local DCT

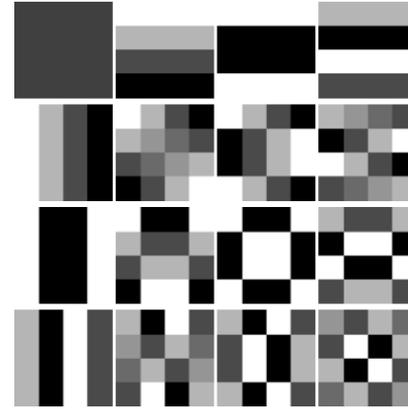
What goes wrong?

# 2D system: tensor product of 1D systems

## ◆ 2D filters (elementary atoms)



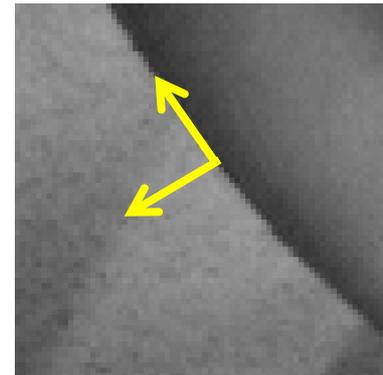
linear spline wavelet



local DCT

What goes wrong?

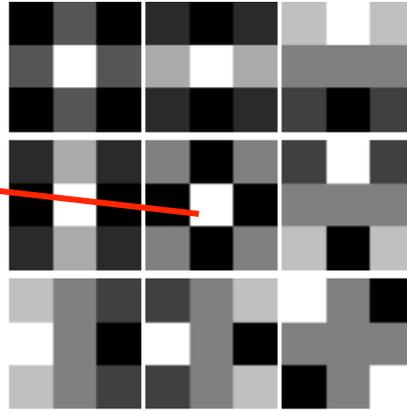
## ◆ Geometrical structures in images



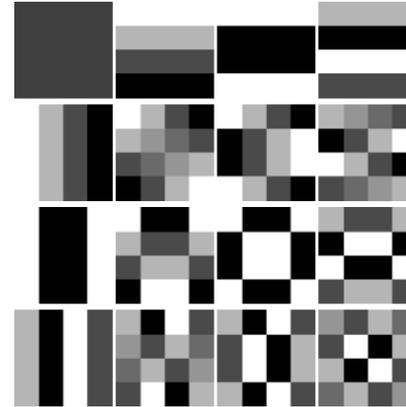
# 2D system: tensor product of 1D systems

## ◆ 2D filters (elementary atoms)

$$\frac{1}{16} \begin{pmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{pmatrix}$$



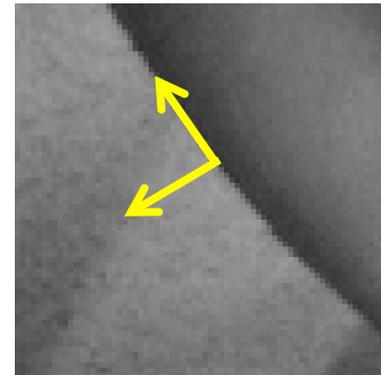
linear spline wavelet



local DCT

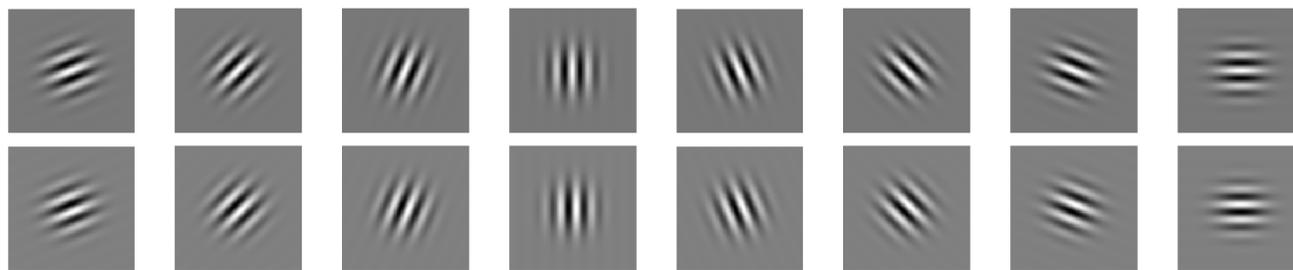
What goes wrong?

## ◆ Geometrical structures in images

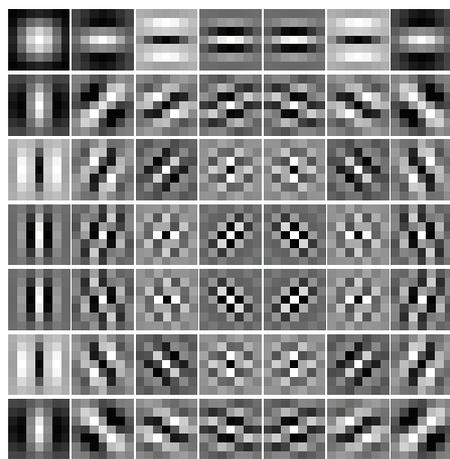


# Gabor function for optimal orientation selectivity

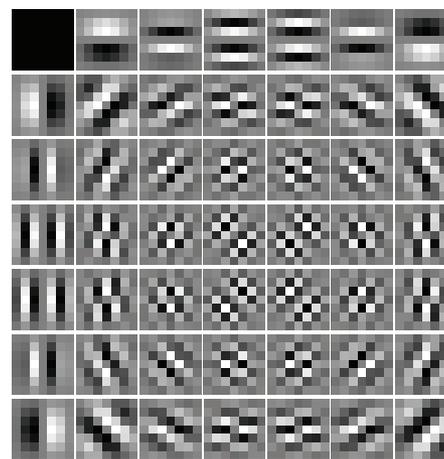
- ◆ 2D tensor product Gabor functions  $g(t_1)g(t_2)e^{2\pi i(\omega_1 t_1 + \omega_2 t_2)}$



- ◆ 2D tensor product Gabor filters  $\mathbf{g}(m)\mathbf{g}(n)e^{2\pi i b(m\ell_1 + n\ell_2)}$



Real( $\mathbf{g}_{\ell_1, \ell_2}$ )



Imag( $\mathbf{g}_{\ell_1, \ell_2}$ )

# Outline of the work

- ◆ Motivation: ideal discrete representation for images
  - ◆ orientation selectivity
  - ◆ local time-frequency analysis
  - ◆ multi-scale structure

# Outline of the work

- ◆ Motivation: ideal discrete representation for images
  - ◆ orientation selectivity
  - ◆ local time-frequency analysis
  - ◆ multi-scale structure
- ◆ Main results
  - ◆ Construction of discrete (tight) frames with Gabor structure
  - ◆ Relationship between digital Gabor filters and MRA-based wavelet tight frames

# Outline of the work

- ◆ Motivation: ideal discrete representation for images
  - ◆ orientation selectivity
  - ◆ local time-frequency analysis
  - ◆ multi-scale structure
- ◆ Main results
  - ◆ Construction of discrete (tight) frames with Gabor structure
  - ◆ Relationship between digital Gabor filters and MRA-based wavelet tight frames
- ◆ Applications in image restoration

# Definitions and notations

$H$  is a Hilbert space.  $\{v_n\}_{n \in I} \subset H$  is

- a *Riesz sequence*: there exists  $C_2 \geq C_1 > 0$  s.t.

$$C_1 \sum_{n \in I} |\mathbf{c}(n)|^2 \leq \left\| \sum_{n \in I} \mathbf{c}(n) v_n \right\|_2^2 \leq C_2 \sum_{n \in I} |\mathbf{c}(n)|^2,$$

for any  $\{\mathbf{c}(n)\}_{n \in I} \in \ell^2(I)$ .

- an *orthonormal sequence*: a Riesz sequence with  $C_1 = C_2 = 1$ .
- a *frame* for  $H$ : there exist  $B \geq A > 0$  s.t.

$$A \|f\|^2 \leq \sum_{n \in I} |\langle f, v_n \rangle|^2 \leq B \|f\|^2, \quad \forall f \in H.$$

- a *tight frame* for  $H$ : a frame with  $A = B = 1$ .
- $\{u_n\}_{n \in I}$  is the *dual frame* of  $\{v_n\}_{n \in I}$ :

$$f = \sum_{n \in I} \langle f, v_n \rangle u_n = \sum_{n \in I} \langle f, u_n \rangle v_n, \quad \forall f \in H.$$

# Characterization of frame property of discrete Gabor systems

◆ *Gabor system*  $X = (K, L)_g$  in  $\mathbb{C}^N$  :

$$\{\mathbf{g}_{k,\ell}(m) = \mathbf{g}((m - ak) \bmod N) e^{-2\pi i \ell b m}, 0 \leq m < N\}_{k \in K, \ell \in L},$$

with  $K := \{0, 1, \dots, N/a - 1\}$ ,  $L := \{0, 1, \dots, b^{-1} - 1\}$ .

◆ Define the *adjoint system* of a Gabor system:

system	$X = (K, L)_g$	$X^* = (L^*, K^*)_g$
shift parameter	$(a, b)$	$(1/b, 1/a)$
lattices	$K = \{0, 1, \dots, N/a - 1\}$ $L = \{0, 1, \dots, b^{-1} - 1\}$	$L^* = \{0, 1, \dots, Nb - 1\}$ $K^* = \{0, 1, \dots, a - 1\}$

# Cont'd

## Theorem 1 (Duality principle)

- I.  $X$  is a frame for  $\mathbb{C}^N$  if and only if  $(ab)^{-\frac{1}{2}} X^*$  is a Riesz sequence;
- II.  $X$  is a tight frame for  $\mathbb{C}^N$  if and only if  $(ab)^{-\frac{1}{2}} X^*$  is an orthonormal sequence

# Cont'd

## Theorem 1 (Duality principle)

- I.  $X$  is a frame for  $\mathbb{C}^N$  if and only if  $(ab)^{-\frac{1}{2}} X^*$  is a Riesz sequence;
- II.  $X$  is a tight frame for  $\mathbb{C}^N$  if and only if  $(ab)^{-\frac{1}{2}} X^*$  is an orthonormal sequence

## Theorem 2 (Construction of Gabor tight frames)

Suppose  $\mathbf{g} \in \mathbb{R}^N$  is non-negative with support  $\{0, 1, \dots, p-1\}$ .

$X = (K, L)_{\mathbf{g}}$  is a tight frame for  $\mathbb{C}^N$  if and only if

$$(i) \quad b \leq p^{-1}; \quad \text{and} \quad (ii) \quad \sum_{k=0}^{N/a-1} (\mathbf{g}((\cdot - ak) \bmod N))^2 \equiv b.$$

# Removing nonzero DC offset of Gabor tight frames

## ◆ Phenomenon of nonzero DC offset

**Example:** Cubic B-spline with nodes  $[0,1,2,3,4]$  and  $a=1, b=1/3$ .

$$\mathbf{g}_0 = \frac{\sqrt{2}}{6}[1,2,1]; \mathbf{g}_1 = \frac{\sqrt{2}}{12}[2,-2,-1] + i\frac{\sqrt{6}}{12}[0,-2,1]; \mathbf{g}_2 = \frac{\sqrt{2}}{12}[2,-2,-1] + i\frac{\sqrt{6}}{12}[0,2,-1].$$

# Removing nonzero DC offset of Gabor tight frames

## ◆ Phenomenon of nonzero DC offset

**Example:** Cubic B-spline with nodes  $[0,1,2,3,4]$  and  $a=1, b=1/3$ .

$$\mathbf{g}_0 = \frac{\sqrt{2}}{6}[1,2,1]; \mathbf{g}_1 = \frac{\sqrt{2}}{12}[2,-2,-1] + i\frac{\sqrt{6}}{12}[0,-2,1]; \mathbf{g}_2 = \frac{\sqrt{2}}{12}[2,-2,-1] + i\frac{\sqrt{6}}{12}[0,2,-1].$$

## ◆ Gabor induced frame with zero DC offset and explicit dual frame

$$\bar{\mathbf{g}}_\ell = e^{i\theta_\ell} \mathbf{g}_\ell - \mu_\ell \mathbf{g}_0$$

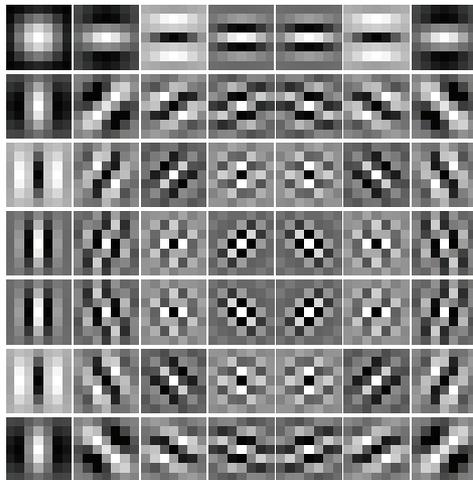
$$\bar{\mathbf{g}}_0 = \frac{\sqrt{2}}{6}[1,2,1]; \bar{\mathbf{g}}_1 = \frac{\sqrt{2}}{8}[-1,2,-1] + i\frac{\sqrt{6}}{12}[1,0,-1]; \bar{\mathbf{g}}_2 = \frac{\sqrt{2}}{8}[-1,2,-1] + i\frac{\sqrt{6}}{12}[-1,0,1].$$

# Analysis of orientation selectivity

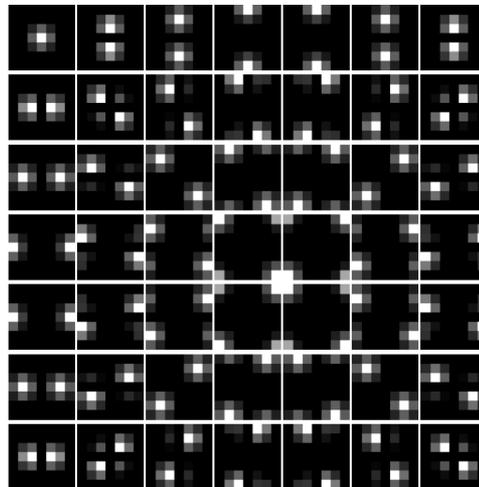
## ◆ Definition 1 (Orientation selectivity)

$\mathbf{h} \in \mathbb{C}^{p \times p}$  has strong selectivity w.r.t. orientation  $\theta$  if

- 1) all maximum points of  $|\hat{\mathbf{h}}|$  are on  $\omega_x \cos \theta + \omega_y \sin \theta = 0$  ;
- 2) the values of  $|\hat{\mathbf{h}}|$  away from  $\omega_x \cos \theta + \omega_y \sin \theta = 0$  are negligible.



$\text{Real}(\mathbf{g}_{j_1, j_2})$ , size  $7 \times 7$



Absolute value of Fourier  
of  $\text{Real}(\mathbf{g}_{j_1, j_2})$

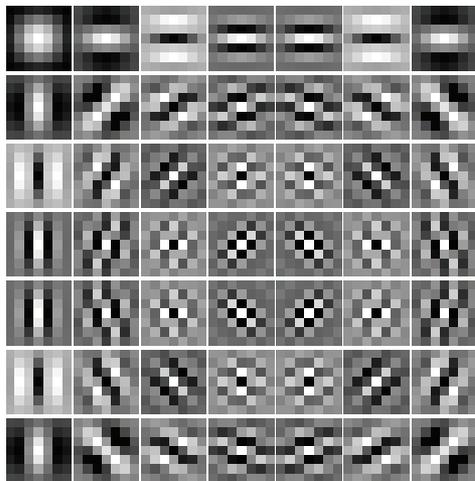
Gabor induced frames

# Analysis of orientation selectivity

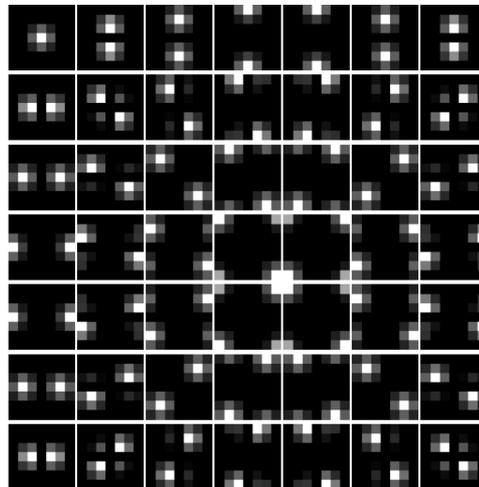
## ◆ Definition 1 (Orientation selectivity)

$\mathbf{h} \in \mathbb{C}^{p \times p}$  has strong selectivity w.r.t. orientation  $\theta$  if

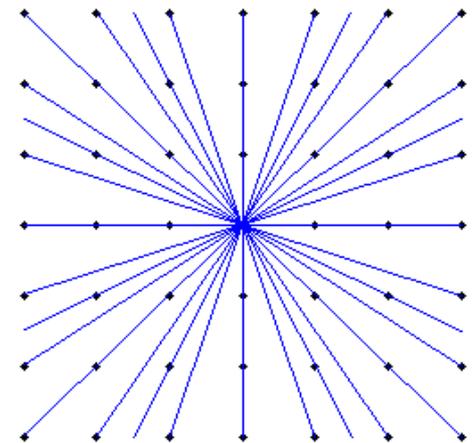
- 1) all maximum points of  $|\hat{\mathbf{h}}|$  are on  $\omega_x \cos \theta + \omega_y \sin \theta = 0$  ;
- 2) the values of  $|\hat{\mathbf{h}}|$  away from  $\omega_x \cos \theta + \omega_y \sin \theta = 0$  are negligible.



$\text{Real}(\mathbf{g}_{j_1, j_2})$ , size  $7 \times 7$



Absolute value of Fourier  
of  $\text{Real}(\mathbf{g}_{j_1, j_2})$



$7 \times 7$

feasible orientations

Gabor induced frames

◆ What we have done:

- Derive duality principle for discrete Gabor systems
- Construct discrete Gabor tight frame and Gabor induced frame providing
  - Local time frequency analysis
  - Optimal orientation selectivity

◆ What we have done:

- Derive duality principle for discrete Gabor systems
- Construct discrete Gabor tight frame and Gabor induced frame providing
  - Local time frequency analysis
  - Optimal orientation selectivity

◆ Question to ask:

Can we introduce the multi-scale property into Gabor systems?

◆ What we have done:

- Derive duality principle for discrete Gabor systems
- Construct discrete Gabor tight frame and Gabor induced frame providing
  - Local time frequency analysis
  - Optimal orientation selectivity

◆ Question to ask:

Can we introduce the multi-scale property into Gabor systems?

◆ Next goal:

Construct MRA-based wavelet tight frame with Gabor structure

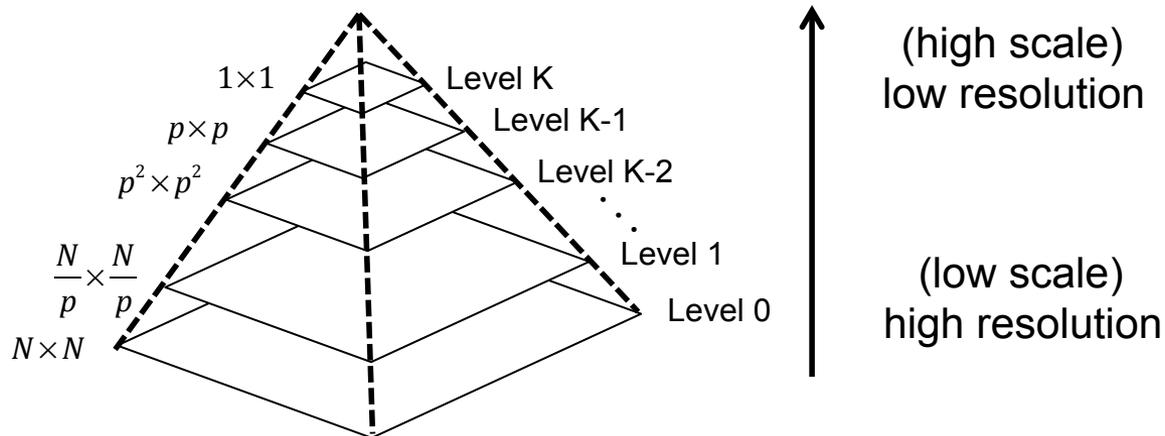
# Multi-resolution analysis (MRA)

- ◆ If  $\phi(t) = p \sum_{k \in \mathbb{Z}} \mathbf{a}_0(k) \phi(pt - k)$ ,  $t \in \mathbb{R}$ ,
  - $p \in \mathbb{Z} (p > 1)$  : *dilation factor*;
  - $\mathbf{a}_0 \in \ell_2(\mathbb{Z})$  : *refinement mask*;
  - $\phi \in L_2(\mathbb{R})$  : *p-dilation refinable function*.
- ◆ Assume  $\phi$  is p-refinable and  $\hat{\phi}(0) = 1$ , define  $\{V_n\}_{n \in \mathbb{Z}}$  by

$$V_n = \overline{\text{span}\{\phi(p^n \cdot -k)\}_{k \in \mathbb{Z}}}.$$

- ◆  $\{V_n\}_{n \in \mathbb{Z}}$  forms a *multi-resolution analysis (MRA)* for  $L_2(\mathbb{R})$  if
  - (i)  $V_n \subset V_{n+1}$ , (ii)  $\overline{\cup_n V_n} = L_2(\mathbb{R})$ , (iii)  $\cap_n V_n = \{0\}$ .

Image  
Pyramid:



# MRA based wavelet system and discrete Gabor filters

◆ By  $\psi_\ell(t) = p \sum_{m \in \mathbb{Z}} \mathbf{a}_\ell(m) \phi(pt - m)$  ( $t \in \mathbb{R}$ ), define:

- $\Psi = \{\psi_\ell\}_{\ell=1}^r$  : a set of *wavelet functions*;
- $\mathbf{a}_\ell \in \ell_2(\mathbb{Z})$  ( $1 \leq \ell \leq r$ ) : *wavelet masks*.

◆ Define *p-dilation wavelet system*  $X(\Psi)$

$$X(\Psi) = \left\{ \psi_{\ell,n,k} \right\}_{\substack{1 \leq \ell \leq r \\ n,k \in \mathbb{Z}}} = \left\{ p^{n/2} \psi_\ell(p^n \cdot -k) \right\}_{\substack{1 \leq \ell \leq r \\ n,k \in \mathbb{Z}}} .$$

◆ Discrete multi-scale wavelet tight frames for  $\ell_2(\mathbb{Z})$  are generated by the filter bank

$$\{\mathbf{a}_0, \mathbf{a}_1, \dots, \mathbf{a}_r\}.$$

# MRA based wavelet system and discrete Gabor filters

◆ By  $\psi_\ell(t) = p \sum_{m \in \mathbb{Z}} \mathbf{a}_\ell(m) \phi(pt - m)$  ( $t \in \mathbb{R}$ ), define:

- $\Psi = \{\psi_\ell\}_{\ell=1}^r$  : a set of *wavelet functions*;
- $\mathbf{a}_\ell \in \ell_2(\mathbb{Z})$  ( $1 \leq \ell \leq r$ ) : *wavelet masks*.

◆ Define *p-dilation wavelet system*  $X(\Psi)$

$$X(\Psi) = \left\{ \psi_{\ell,n,k} \right\}_{\substack{1 \leq \ell \leq r \\ n,k \in \mathbb{Z}}} = \left\{ p^{n/2} \psi_\ell(p^n \cdot -k) \right\}_{\substack{1 \leq \ell \leq r \\ n,k \in \mathbb{Z}}} .$$

◆ Discrete multi-scale wavelet tight frames for  $\ell_2(\mathbb{Z})$  are generated by the filter bank

$$\{\mathbf{a}_0, \mathbf{a}_1, \dots, \mathbf{a}_r\}.$$

**Question:** can these filter be replaced by Gabor filters with orientation selectivity?

**Window:**  $\mathbf{g}(m) = 0$  if  $m \notin [0, q - 1]$ , **masks:**  $\{\mathbf{g}_\ell(m) = \mathbf{g}(m) e^{-2\pi i b \ell m}\}_{\ell=0}^{1/b-1}$

# Answer

## Theorem 4 (UEP based characterization of Gabor filters induced wavelet tight frames)

$\phi$  defined from  $\mathbf{g}$  generates an MRA for  $L_2(\mathbb{R})$  and  $X(\Psi)$  form a tight frame for  $L_2(\mathbb{R})$ , if the followings hold true:

1.  $\frac{1}{b} \geq q$ ;

2.  $\sum_{n \in \mathbb{Z}} \mathbf{g}(n) = 1$ ;

3.  $\sum_{n \in \Omega_j} |\mathbf{g}(n)|^2 = \frac{b}{p}$ , where  $j \in \mathbb{Z} / p\mathbb{Z}$ ,  $\Omega_j = (p\mathbb{Z} + j) \cap \text{supp}(\mathbf{g})$ .

# Answer

## Theorem 4 (UEP based characterization of Gabor filters induced wavelet tight frames)

$\phi$  defined from  $\mathbf{g}$  generates an MRA for  $L_2(\mathbb{R})$  and  $X(\Psi)$  form a tight frame for  $L_2(\mathbb{R})$ , if the followings hold true:

1.  $\frac{1}{b} \geq q$ ;

2.  $\sum_{n \in \mathbb{Z}} \mathbf{g}(n) = 1$ ;

3.  $\sum_{n \in \Omega_j} |\mathbf{g}(n)|^2 = \frac{b}{p}$ , where  $j \in \mathbb{Z} / p\mathbb{Z}$ ,  $\Omega_j = (p\mathbb{Z} + j) \cap \text{supp}(\mathbf{g})$ .

### ◆ Unitary Extension Principle (UEP, [1])

Let  $\phi \in L_2(\mathbb{R})$  be refinable with  $\hat{\phi}(0) = 1$ , and  $\mathbf{a}_0$  is finitely supported  
Then  $X(\Psi)$  forms a tight frame for  $L_2(\mathbb{R})$ , if for any  $v \in p^{-1}\mathbb{Z} \setminus \mathbb{Z}$

$$\sum_{\ell=0}^r \hat{\mathbf{a}}_{\ell}(\omega) \overline{\hat{\mathbf{a}}_{\ell}(\omega + 2\pi v)} = \delta(v), \quad \text{a.e. } \omega \in [-\pi, \pi]$$

## Cont'd

### Theorem 5 (Solutions to UEP-based characterization)

Finitely supported window  $\mathbf{g}$  satisfies Condition 1, 2, 3 for some  $b$ , if and only if  $\mathbf{g} = b(\dots, 0, 0, \underbrace{1, \dots, 1}_{1/b}, 0, \dots)$  and  $\frac{1}{bp} \in \mathbb{Z}$ .

### Theorem 6 (Refinable functions in continuum space)

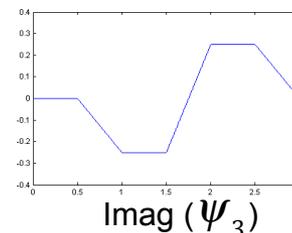
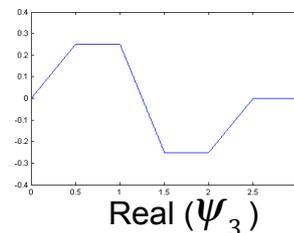
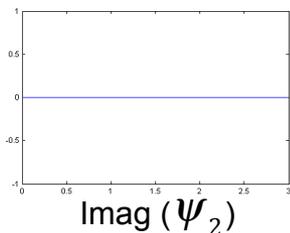
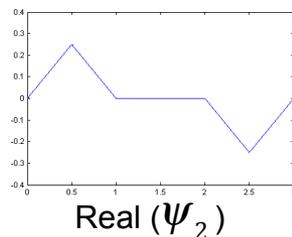
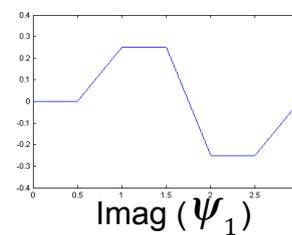
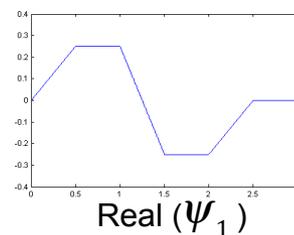
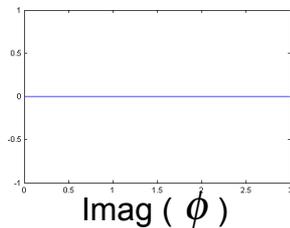
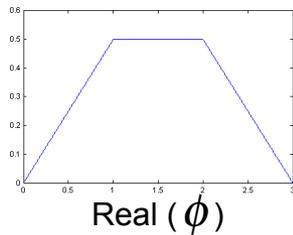
$\phi$  is refinable with  $\hat{\phi}(0) = 1$ , and  $\mathbf{g} = p^{-k}(1, \dots, 1) \in \mathbb{R}^{p^k}$  ( $k \geq 2$ )

Then  $\phi$  is a  $(k-1)$ th order spline.

# Example

## ◆ Example 2

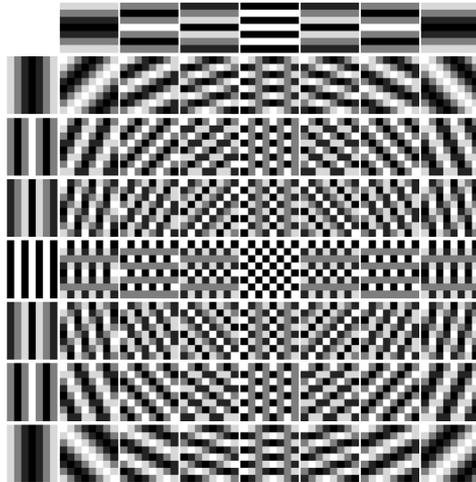
$$p=2, \quad \text{masks:} \quad \left\{ \begin{array}{l} \sigma_0 = \left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right) \\ \sigma_1 = \left(\frac{1}{4}, -\frac{1}{4}i, -\frac{1}{4}, \frac{1}{4}i\right) \\ \sigma_2 = \left(\frac{1}{4}, -\frac{1}{4}, \frac{1}{4}, -\frac{1}{4}\right) \\ \sigma_3 = \left(\frac{1}{4}, \frac{1}{4}i, -\frac{1}{4}, -\frac{1}{4}i\right) \end{array} \right. \quad \phi(t) = \begin{cases} \frac{1}{2}t, & t \in [0,1), \\ \frac{1}{2}, & t \in [1,2), \\ \frac{1}{2}(3-t), & t \in [2,3), \\ 0, & \text{otherwise.} \end{cases}$$



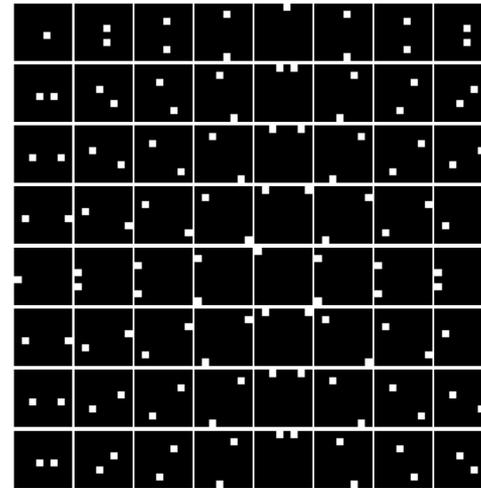
# Example

## ◆ Example 3

$p=8$ , refinable mask:  $\mathbf{g} = \left(\frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}, \frac{1}{8}\right)$



Real( $\mathbf{g}_{j_1, j_2}$ ), size  $8 \times 8$



Absolute value of Fourier  
of Real( $\mathbf{g}_{j_1, j_2}$ )

# Application: sparsity based image restoration

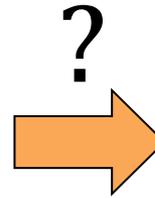
Observation:



Blurred



Noisy



Truth:

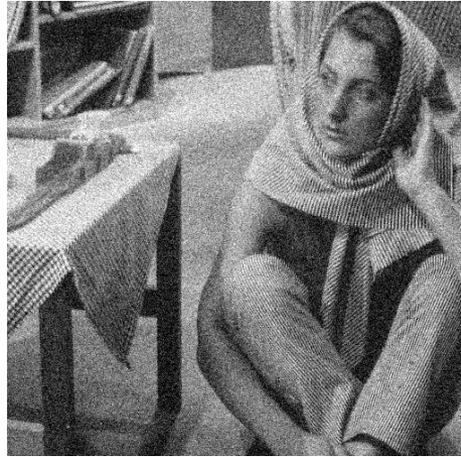


# Application: sparsity based image restoration

Observation:

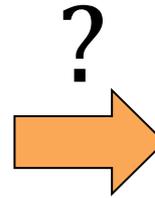


Blurred



Noisy

Truth:



- ◆ Solve linear system

$$\mathbf{b} = \mathbf{A}\mathbf{f} + \mathbf{n},$$

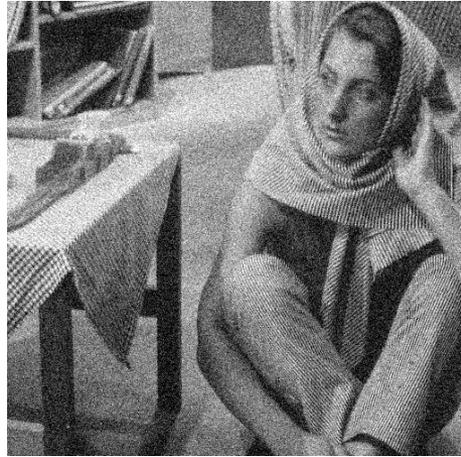
where  $\mathbf{b}$  is the observation,  $\mathbf{f}$  is the truth and  $\mathbf{n}$  is the noise.

# Application: sparsity based image restoration

Observation:



Blurred



Noisy

Truth:



- ◆ Solve linear system

$$\mathbf{b} = \mathbf{A}\mathbf{f} + \mathbf{n},$$

where  $\mathbf{b}$  is the observation,  $\mathbf{f}$  is the truth and  $\mathbf{n}$  is the noise.

- ◆ Suppose  $\mathbf{f} = \sum_{n \in I} c_n \mathbf{v}_n = \mathbf{W}_X^* \mathbf{c}$ , and  $\mathbf{c} = \mathbf{W}_Y \mathbf{f}$  is sparse.

# Image recovery using proposed (tight) frame

Recovered image  $\hat{\mathbf{u}} = \sum_{k=1}^m \mathbf{u}_k$  is solved from *sparsity based multi-layer composite model*,

$$\min_{\{\mathbf{u}_1, \dots, \mathbf{u}_m\} \subset \mathbb{R}^N} \sum_{k=1}^m \lambda_k \|\mathbf{W}_{Y_k} \mathbf{u}_k\|_1, \quad \text{s.t.} \quad \|\mathbf{A}(\sum_{k=1}^m \mathbf{u}_k) - \mathbf{b}\|_2 \leq \epsilon,$$

# Image recovery using proposed (tight) frame

Recovered image  $\hat{\mathbf{u}} = \sum_{k=1}^m \mathbf{u}_k$  is solved from *sparsity based multi-layer composite model*,

$$\min_{\{\mathbf{u}_1, \dots, \mathbf{u}_m\} \subset \mathbb{R}^N} \sum_{k=1}^m \lambda_k \|\mathbf{W}_{Y_k} \mathbf{u}_k\|_1, \quad \text{s.t.} \quad \|\mathbf{A}(\sum_{k=1}^m \mathbf{u}_k) - \mathbf{b}\|_2 \leq \epsilon,$$

## ◆ Proposed and comparison methods:

- $Y_1$ : Gabor induced frame by cubic B-spline  $a = 2, b = 1/7, L = 7$ ;
- $Y_2$ : Gabor induced frame by cubic B-spline  $a = 4, b = 1/15, L = 15$ .
- $Y_1$ : MRA based wavelet tight frame with Gabor structure  $p = 2, b = 1/8, L = 8$ .

# Results

Table 1: PSNR values of denoised images

image	TV [1]	Linear spline framelet [2]	DT-CWT [3]	Multi Gabor induced frame	tight frame w / p=8
Barbara	26.84	29.25	28.90	<b>30.39</b>	29.38
Bowl	29.24	30.15	29.43	<b>30.58</b>	30.40
Cameraman	28.83	29.00	28.94	29.26	<b>29.29</b>
Lena	30.71	31.10	31.49	<b>31.74</b>	31.39

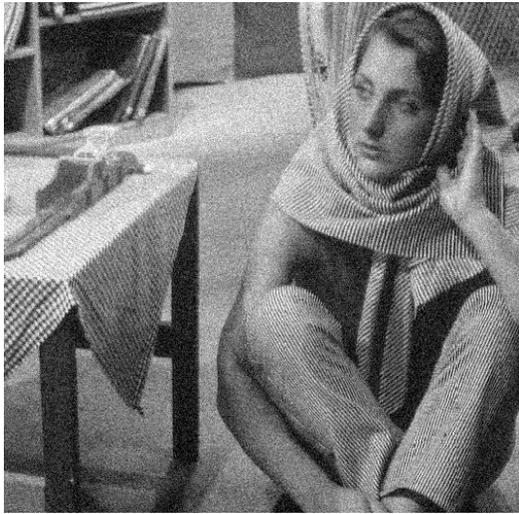
---

[1] Y. Wang, J. Yang, W. Yin, Y. Zhang, A new alternating minimization algorithm for total variation image reconstruction, SIAM J. Imaging Sci. 2008

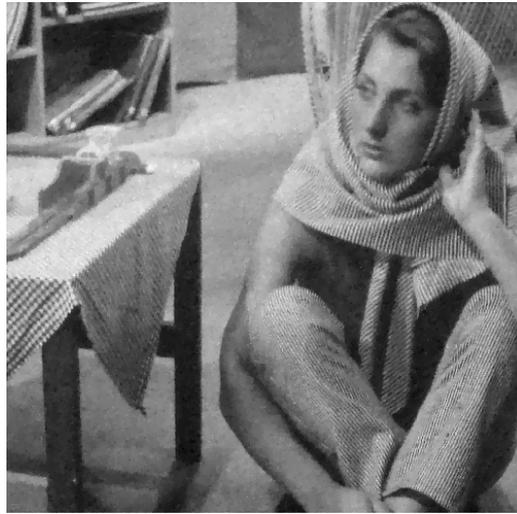
[2] J. Cai, S. Osher, Z. Shen, Split Bregman methods and frame based image restoration, SIAM J: Multiscale Model. Sim. 2009

[3] I. W. Selesnick, R. G. Baraniuk, N. C. Kingsbury, The dual-tree complex wavelet transform, IEEE Signal Proc. Mag. 2005

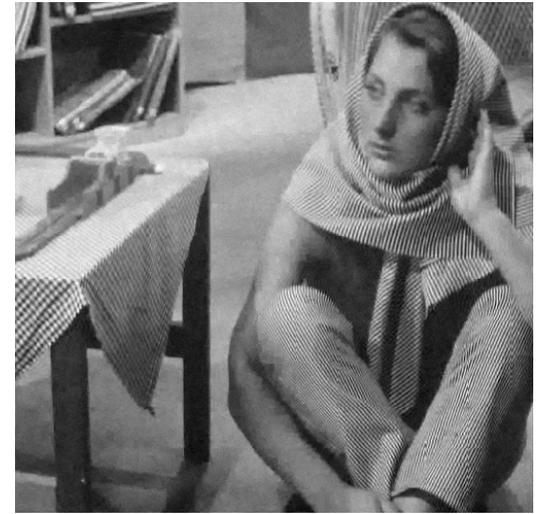
# Results



(a) noisy image,  $\sigma = 20$



(b) TV



(c) framelet



(d) DT-CWT



(e) Gabor induced frame



(c) tight frame with  $p=8$

# Results



(a) noisy image,  $\sigma = 20$



(b) TV



(c) framelet



(d) DT-CWT



(e) Gabor induced frame



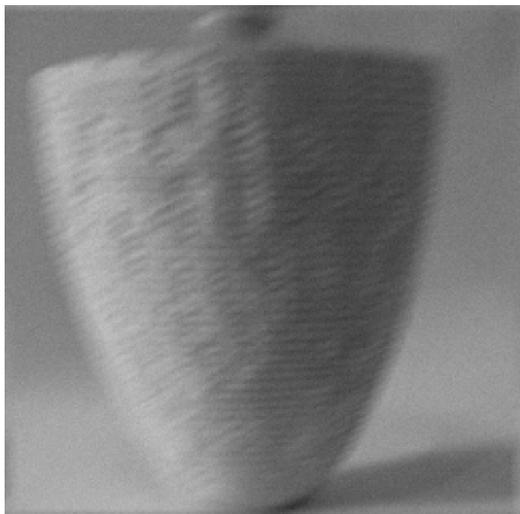
(c) tight frame with  $p=8$

# Results

Table 2: PSNR values of deblurred images

image	kernel	TV	linear spline framelet	DT-CWT	multi Gabor induced frame	tight frame $w / p=8$
Barbara	disk	24.77	25.17	25.15	<b>25.65</b>	25.48
	motion	24.64	24.97	25.00	<b>25.70</b>	25.49
	gaussian	24.13	24.14	24.19	<b>24.21</b>	24.18
	average	23.99	24.03	24.07	<b>24.27</b>	24.10
Bowl	disk	28.73	28.92	28.99	<b>29.35</b>	29.13
	motion	28.88	29.08	29.15	<b>29.67</b>	29.36
	gaussian	27.96	27.82	28.32	<b>28.66</b>	28.46
	average	28.73	28.84	28.94	<b>29.25</b>	29.21
Cameraman	disk	26.31	26.83	26.22	<b>27.01</b>	26.73
	motion	26.18	<b>27.14</b>	26.35	26.93	26.72
	gaussian	24.96	24.84	24.73	<b>25.04</b>	24.94
	average	25.08	25.12	25.00	<b>25.55</b>	25.30
Lena	disk	32.05	32.17	32.25	<b>32.53</b>	32.06
	motion	30.86	30.49	31.21	<b>31.43</b>	30.45
	gaussian	31.34	31.26	31.59	<b>31.74</b>	31.55
	average	30.10	29.96	30.21	<b>30.36</b>	30.06

# Results



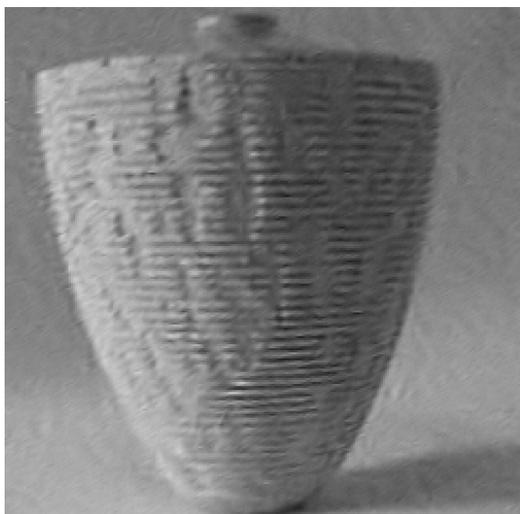
(a) motion blurred image,  $\sigma = 3$



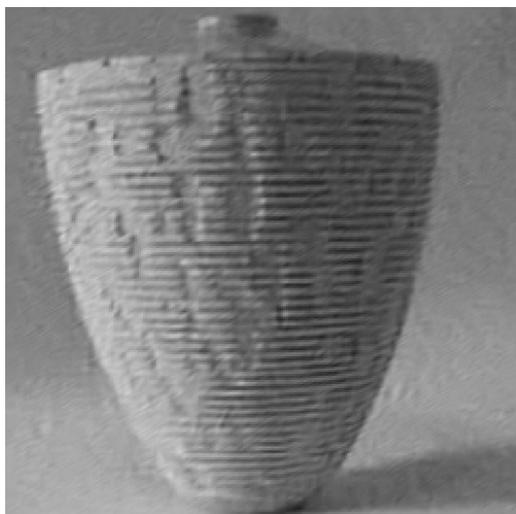
(b) TV



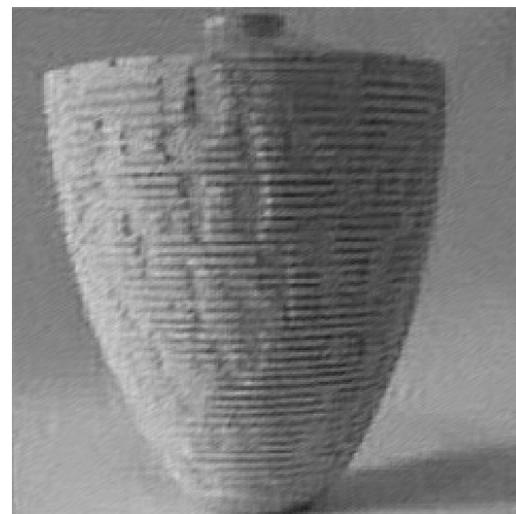
(c) framelet



(d) DT-CWT



(e) Gabor induced frame



(c) tight frame with  $p=8$

# Results



(a) average blur kernel,  $\sigma = 3$



(b) TV



(c) framelet



(d) DT-CWT



(e) Gabor induced frame



(c) tight frame with  $p=8$

# Reference

- H. Ji, Z. Shen, Y. Zhao, Directional frames for image recovery: multi-scale discrete Gabor frames, J. Fourier Anal. Appl. 2016
- H. Ji, Z. Shen, Y. Zhao, Digital Gabor filters that generate MRA-based wavelet tight frames, manuscript

Thank you.