

# Directional Haar Wavelet Frames on Triangles

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# Outline

- 1 Introduction
- 2 Construction of scaling functions
- 3 Construction of directional wavelets
- 4 Applications to image processing

# Motivation

## Basic problem

Construction of a simple system  $\{e_i : i \in I\}$  such that every function  $f$  of a certain class can be represented by

$$f = \sum_{i \in I} \langle f, e_i \rangle e_i.$$

## 2D-signals (images)

Traditional approach with tensor product wavelets

$$f(x_1, x_2) = \sum_{(i,j) \in I} \langle f, \psi_i \psi_j \rangle \psi_i(x_1) \psi_j(x_2)$$

Important drawback: no rotation invariance  $\rightarrow$  no optimal representation of images with orientated discontinuous structures

# Successful approaches

## X-lets

### • Contourlets

- ▶ M.N. Do & M. Vetterli, *The contourlet transform: an efficient directional multiresolution image representation*, IEEE Trans. Image Process. **14**(12) (2005), 2091–2106.
- ▶ D.D. Po & M.N. Do, *Directional multiscale modeling of images using the contourlet transform*, IEEE Trans. Image Process. **15** (2006), 1610–1620.

### • Curvelets

- ▶ E.J. Candès & D.L. Donoho, *Curvelets – a suprisingly effective nonadaptive representation for objects with edges*, in: Curves and Surfaces, C. Rabut, A. Cohen and L.L. Schumaker (Eds.), Vanderbilt University Press, Nashville, 2000, 105–120.
- ▶ E.J. Candès & D.L. Donoho, *New tight frames of curvelets and optimal representations of objects with piecewise  $C^2$  singularities*, Comm. Pure and Appl. Math. **56** (2004), 216–266.

### • Shearlets

- ▶ K. Guo, W.-Q. Lim, D. Labate, G. Weiss, & E. Wilson, *Wavelets with composite dilations and their MRA properties*, Appl. Comput. Harmon. Anal. **20** (2006), 231–249.
- ▶ K. Guo & D. Labate, *Optimally sparse multidimensional representation using shearlets*, SIAM J. Math. Anal. **39** (2007), 298–318.

## Drawbacks

- Compact support in Fourier domain
- No multiresolution analysis (MRA) associated

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## Domain division

Consider the domain  $\Omega := [-1, 1]^2$  and divide it into 16 triangles with the same area.

$$U_0 := \text{conv}\left\{\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1/2 \\ 1 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}\right\}$$

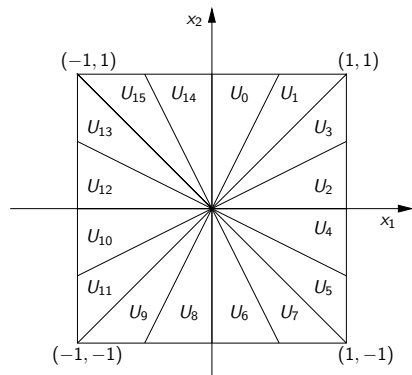
$$U_1 := \text{conv}\left\{\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1/2 \\ 1 \end{pmatrix}\right\}$$

Group of isometries of the square  $[-1, 1]^2$ :  
 $\mathcal{B} := \{B_i : i = 0, \dots, 7\}$  with

$$B_0 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, B_1 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, B_2 = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix},$$

$$B_3 = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}, B_4 = \begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix},$$

$$B_5 = \begin{pmatrix} 0 & -1 \\ -1 & 0 \end{pmatrix}, B_6 = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}, B_7 = \begin{pmatrix} -1 & 0 \\ 0 & 1 \end{pmatrix}.$$



For  $i = 0, \dots, 7$ :

$$U_{2i} = \{B_i^{-1}x : x \in U_0\} = B_i^{-1}U_0,$$

$$U_{2i+1} = \{B_i^{-1}x : x \in U_1\} = B_i^{-1}U_1.$$

## Construction of scaling functions

Define on the triangles  $U_i$  *nonseparable scaling functions of Haar type*

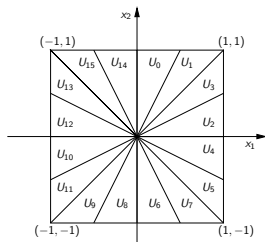
$$\phi_0(x) = \phi_0(x_1, x_2) := \chi_{U_0}(x_1, x_2) = \chi_{[0,1]}\left(\frac{2x_1}{x_2}\right) \cdot \chi_{[0,1]}(x_2),$$

$$\phi_1(x) = \phi_1(x_1, x_2) := \chi_{U_1}(x_1, x_2) = \chi_{[1,2]}\left(\frac{2x_1}{x_2}\right) \cdot \chi_{[0,1]}(x_2).$$

In general for  $i = 0, \dots, 7$ :

$$\phi_{2i}(x) := \phi_0(B_i x) = \chi_{U_0}(B_i x) = \chi_{B_i^{-1}U_0}(x) = \chi_{U_{2i}}(x),$$

$$\phi_{2i+1}(x) := \phi_1(B_i x) = \chi_{U_1}(B_i x) = \chi_{B_i^{-1}U_1}(x) = \chi_{U_{2i+1}}(x).$$



## MRA properties of scaling functions

Besides *rotation/reflection*  $i \in \{0, \dots, 7\}$  consider *dilations*  $j \in \mathbb{Z}$  and *translations*  $k \in \mathbb{Z}^2$ :

$$\begin{aligned}\phi_{2^i,j,k}(x) &:= 2^j \phi_0(B_i(2^j x - k)), \\ \phi_{2^{i+1},j,k}(x) &:= 2^j \phi_1(B_i(2^j x - k)).\end{aligned}$$

The sequence  $\{V_j\}_{j \in \mathbb{Z}}$  of subspaces of  $L^2(\mathbb{R}^2)$ , given by

$$V_j := \text{clos}_{L^2(\mathbb{R}^2)} \text{span}\{\phi_{2^i,j,k}, \phi_{2^{i+1},j,k} : i = 0, \dots, 7; k \in \mathbb{Z}^2\},$$

forms a generalized, stationary multiresolution analysis (MRA) of  $L^2(\mathbb{R}^2)$ . For the following properties are satisfied:

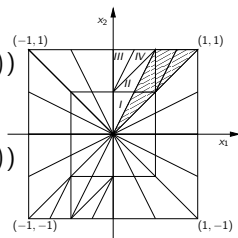
- 1  $V_j \subset V_{j+1} \quad \forall j \in \mathbb{Z}$ .
- 2  $\bigcap_{j \in \mathbb{Z}} V_j = \{0\}$ .
- 3  $\text{clos}_{L^2(\mathbb{R}^2)} \bigcup_{j \in \mathbb{Z}} V_j = L^2(\mathbb{R}^2)$ .
- 4  $\{\phi_{2^i}(\cdot - k), \phi_{2^{i+1}}(\cdot - k) : i = 0, \dots, 7; k \in \mathbb{Z}^2\}$  forms a frame of  $V_0$ .



## Refinability of scaling functions

Two-scale relations for  $\phi_0$  and  $\phi_1$  ( $V_0 \subset V_1$ )

$$\begin{aligned}\phi_0 &= \phi_0(2\cdot) + \phi_0(2\cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}) + \phi_1(2\cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}) + \phi_9(2\cdot - \begin{pmatrix} 1 \\ 2 \end{pmatrix}) \\ &= \frac{1}{2} \left( \phi_{0,1, \begin{pmatrix} 0 \\ 0 \end{pmatrix}} + \phi_{0,1, \begin{pmatrix} 0 \\ 1 \end{pmatrix}} + \phi_{1,1, \begin{pmatrix} 0 \\ 1 \end{pmatrix}} + \phi_{9,1, \begin{pmatrix} 1 \\ 2 \end{pmatrix}} \right) \\ \phi_1 &= \phi_1(2\cdot) + \phi_1(2\cdot - \begin{pmatrix} 1 \\ 1 \end{pmatrix}) + \phi_0(2\cdot - \begin{pmatrix} 1 \\ 1 \end{pmatrix}) + \phi_8(2\cdot - \begin{pmatrix} 1 \\ 2 \end{pmatrix}) \\ &= \frac{1}{2} \left( \phi_{1,1, \begin{pmatrix} 0 \\ 0 \end{pmatrix}} + \phi_{1,1, \begin{pmatrix} 1 \\ 1 \end{pmatrix}} + \phi_{0,1, \begin{pmatrix} 1 \\ 1 \end{pmatrix}} + \phi_{8,1, \begin{pmatrix} 1 \\ 2 \end{pmatrix}} \right).\end{aligned}$$



Two-scale relations for  $i = 0, \dots, 7$

$$\begin{aligned}\phi_{2i} &= \phi_0(B_i \cdot) = \phi_0(2B_i \cdot) + \phi_0(2B_i \cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}) + \phi_1(2B_i \cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}) + \phi_1(B_4(2B_i \cdot - \begin{pmatrix} 1 \\ 2 \end{pmatrix})) \\ &= \frac{1}{2} \left( \phi_{2i,1, \begin{pmatrix} 0 \\ 0 \end{pmatrix}} + \phi_{2i,1, B_i^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}} + \phi_{2i+1,1, B_i^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}} + \phi_{(2i+9) \bmod 16, 1, B_i^{-1} \begin{pmatrix} 1 \\ 2 \end{pmatrix}} \right) \\ \phi_{2i+1} &= \frac{1}{2} \left( \phi_{2i+1,1, \begin{pmatrix} 0 \\ 0 \end{pmatrix}} + \phi_{2i+1,1, B_i^{-1} \begin{pmatrix} 1 \\ 1 \end{pmatrix}} + \phi_{2i,1, B_i^{-1} \begin{pmatrix} 1 \\ 1 \end{pmatrix}} + \phi_{(2i+8) \bmod 16, 1, B_i^{-1} \begin{pmatrix} 1 \\ 2 \end{pmatrix}} \right).\end{aligned}$$

General two-scale relations for  $i = 0, \dots, 7, j \in \mathbb{Z}, k \in \mathbb{Z}^2$  ( $V_j \subset V_{j+1}$ )

$$\begin{aligned}\phi_{2i,j,k} &= \frac{1}{2} \left( \phi_{2i,j+1,2k} + \phi_{2i,j+1,2k+B_i^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}} + \phi_{2i+1,j+1,2k+B_i^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}} + \right. \\ &\quad \left. + \phi_{(2i+9) \bmod 16, j+1, 2k+B_i^{-1} \begin{pmatrix} 1 \\ 2 \end{pmatrix}} \right)\end{aligned}$$

## Frame condition

### Definition (frame)

A countable family of elements  $\{e_i : i \in I\}$  in  $V$  is a *frame* for  $V$  if there exist constants  $A, B > 0$  such that

$$A \|f\|_{L^2(\mathbb{R}^2)}^2 \leq \sum_{i \in I} |\langle f, e_i \rangle|^2 \leq B \|f\|_{L^2(\mathbb{R}^2)}^2.$$

$A, B$  are called *frame bounds*. A frame is *tight* if we can choose  $A = B$ .

### Determination of frame bounds $A, B$

The frame bounds  $A, B$  can be got by the eigenvalues of the frame operator  $S$ . The optimal lower frame bound  $A$  is the smallest eigenvalue for  $S$ , and the optimal upper frame bound  $B$  is the largest eigenvalue.

In finite-dimensional spaces we can consider the eigenvalues of the Gramian matrix  $G$  instead of  $S$ .

## Frame condition

The family of the 16 functions  $\{\phi_i(\cdot - k) : i = 0, \dots, 15; k \in \mathbb{Z}^2\}$  provide the following Gram matrix:

$$G := (\langle \phi_i, \phi_{i'} \rangle)_{i, i'=0}^{15} = \frac{1}{4} \begin{pmatrix} I_4 & G_1 & G_2 & G_1^T \\ G_1^T & I_4 & G_1 & G_2 \\ G_2 & G_1^T & I_4 & G_1 \\ G_1 & G_2 & G_1^T & I_4 \end{pmatrix} \in \mathbb{R}^{16 \times 16}$$

with the identity matrix  $I_4$  of size  $4 \times 4$  and with certain matrices  $G_1$  and  $G_2$ .

Observation:

- $\text{rank}(G) = 11$ .
- smallest and largest eigenvalues of  $G$  provide the frame bounds  $A \approx 0.0745$  and  $B = 1$ .

$\implies \{\phi_i(\cdot - k) : i = 0, \dots, 15; k \in \mathbb{Z}^2\}$  is a frame of  $V_0$ , i.e. it holds the inequality

$$A \|f\|_{L^2(\mathbb{R}^2)}^2 \leq \sum_{i=0}^{15} \sum_{k \in \mathbb{Z}^2} |\langle f, \phi_i(\cdot - k) \rangle|^2 \leq B \|f\|_{L^2(\mathbb{R}^2)}^2 \quad \forall f \in V_0.$$

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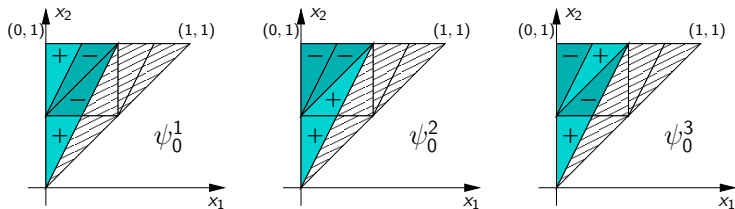
## Construction of directional wavelet functions

The locality and refinability of generating functions  $\phi_0$  imply to consider the following wavelet functions:

$$\psi_0^1(x) = \frac{1}{2} \left( \phi_{0,1,\binom{0}{0}}(x) + \phi_{0,1,\binom{0}{1}}(x) - \phi_{1,1,\binom{0}{1}}(x) - \phi_{9,1,\binom{1}{2}}(x) \right),$$

$$\psi_0^2(x) = \frac{1}{2} \left( \phi_{0,1,\binom{0}{0}}(x) - \phi_{0,1,\binom{0}{1}}(x) - \phi_{1,1,\binom{0}{1}}(x) + \phi_{9,1,\binom{1}{2}}(x) \right),$$

$$\psi_0^3(x) = \frac{1}{2} \left( \phi_{0,1,\binom{0}{0}}(x) - \phi_{0,1,\binom{0}{1}}(x) + \phi_{1,1,\binom{0}{1}}(x) - \phi_{9,1,\binom{1}{2}}(x) \right).$$



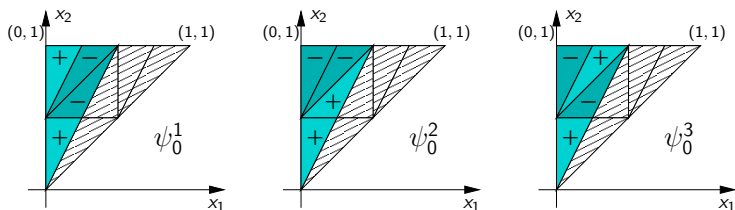
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$$\psi_0^2(x) = \frac{1}{2} \left( \phi_{0,1,\binom{0}{0}}(x) - \phi_{0,1,\binom{0}{1}}(x) - \phi_{1,1,\binom{0}{1}}(x) + \phi_{9,1,\binom{1}{2}}(x) \right),$$

$$\psi_0^3(x) = \frac{1}{2} \left( \phi_{0,1,\binom{0}{0}}(x) - \phi_{0,1,\binom{0}{1}}(x) + \phi_{1,1,\binom{0}{1}}(x) - \phi_{9,1,\binom{1}{2}}(x) \right).$$



In general, regarding rotations  $i = 0, \dots, 7$ , dilations  $j \in \mathbb{Z}$ , and translations  $k \in \mathbb{Z}^2$ , we get for  $r = 1, 2, 3$

$$\psi_{2^j i, j, k}^r := 2^j \psi_0^r(B_i(2^j \cdot -k)) \quad \text{and} \quad \psi_{2^j i+1, j, k}^r := 2^j \psi_1^r(B_i(2^j \cdot -k)).$$

Note: These functions can be understood as wavelets with composite dilations  $(A = 2I, B \in \mathcal{B})$ .

## Wavelet spaces

Wavelet spaces:  $W_j := \text{clos}_{L^2(\mathbb{R}^2)} \text{span} \{ \psi_{i,j,k}^r : i = 0, \dots, 15; r = 1, 2, 3; k \in \mathbb{Z}^2 \}$

$$\implies V_{j+1} = V_j \oplus W_j \quad \forall j \in \mathbb{Z}$$

①  $W_j \subset V_{j+1} \quad \forall j \in \mathbb{Z}$ , for general refinement equations hold:

$$\psi_{2i,j,k}^1 = \frac{1}{2} \left( \phi_{2i,j+1,2k} + \phi_{2i,j+1,2k+B_i^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}} - \phi_{2i+1,j+1,2k+B_i^{-1} \begin{pmatrix} 0 \\ 1 \end{pmatrix}} - \phi_{(2i+9) \bmod 16, j+1, 2k+B_i^{-1} \begin{pmatrix} 1 \\ 2 \end{pmatrix}} \right)$$

and analogous relations for  $\psi_{i,j,k}^2$  and  $\psi_{i,j,k}^3$ .

②  $V_{j+1} = V_j + W_j \quad \forall j \in \mathbb{Z}$ , for reconstruction formulas hold.

$$\begin{aligned} \text{E.g.} \quad \phi_{0,j+1,2k} &= \frac{1}{2} (\phi_{0,j,k} + \psi_{0,j,k}^1 + \psi_{0,j,k}^2 + \psi_{0,j,k}^3), \\ \phi_{0,j+1,2k+\begin{pmatrix} 0 \\ 1 \end{pmatrix}} &= \frac{1}{2} (\phi_{0,j,k} + \psi_{0,j,k}^1 - \psi_{0,j,k}^2 - \psi_{0,j,k}^3). \end{aligned}$$

...

## Wavelet spaces

Wavelet spaces:  $W_j := \text{clos}_{L^2(\mathbb{R}^2)} \text{span} \{ \psi_{i,j,k}^r : i = 0, \dots, 15; r = 1, 2, 3; k \in \mathbb{Z}^2 \}$

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and analogous relations for  $\psi_{i,j,k}^2$  and  $\psi_{i,j,k}^3$ .

②  $V_{j+1} = V_j + W_j \quad \forall j \in \mathbb{Z}$ , for reconstruction formulas hold.

$$\begin{aligned} \text{E.g.} \quad \phi_{0,j+1,2k} &= \frac{1}{2} (\phi_{0,j,k} + \psi_{0,j,k}^1 + \psi_{0,j,k}^2 + \psi_{0,j,k}^3), \\ \phi_{0,j+1,2k+\begin{pmatrix} 0 \\ 1 \end{pmatrix}} &= \frac{1}{2} (\phi_{0,j,k} + \psi_{0,j,k}^1 - \psi_{0,j,k}^2 - \psi_{0,j,k}^3). \\ &\dots \end{aligned}$$

Goal: The set of directional Haar wavelets

$$\Psi_{DH} := \{ \psi_{i,j,k}^r : i = 0, \dots, 15; r = 1, 2, 3; j \in \mathbb{Z}; k \in \mathbb{Z}^2 \}$$

forms a Parseval frame of  $L^2(\mathbb{R}^2)$ .

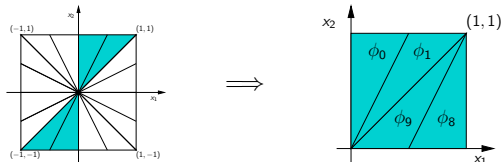


## Tight wavelet frame

Consider the subspaces  $V_j^0, V_j^1, V_j^2,$  and  $V_j^3$  of  $V_j$  given by

$$V_j^\nu := \text{clos}_{L^2(\mathbb{R}^2)} \text{span} \{ \phi_{2^\nu, j, k}, \phi_{2^{\nu+1}, j, k}, \phi_{2^{\nu+8}, j, k}, \phi_{2^{\nu+9}, j, k} : k \in \mathbb{Z}^2 \}, \quad \nu = 0, 1, 2, 3.$$

- The generating functions form an orthogonal basis of  $V_j^\nu$ , where  $\|\phi_{i, j, k}\|_{L^2(\mathbb{R}^2)}^2 = \frac{1}{4}$ ,  $i = 0, \dots, 15; j \in \mathbb{Z}; k \in \mathbb{Z}^2$ .
- $\{V_j^\nu\}_{j \in \mathbb{Z}}$  themselves already form a multiresolution of  $L^2(\mathbb{R}^2)$ .

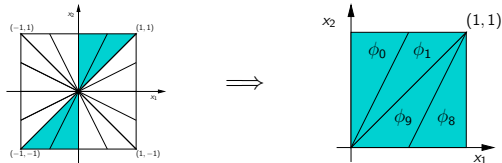


## Tight wavelet frame

Consider the subspaces  $V_j^0$ ,  $V_j^1$ ,  $V_j^2$ , and  $V_j^3$  of  $V_j$  given by

$$V_j^\nu := \text{clos}_{L^2(\mathbb{R}^2)} \text{span} \{ \phi_{2^\nu, j, k}, \phi_{2^{\nu+1}, j, k}, \phi_{2^{\nu+8}, j, k}, \phi_{2^{\nu+9}, j, k} : k \in \mathbb{Z}^2 \}, \quad \nu = 0, 1, 2, 3.$$

- The generating functions form an orthogonal basis of  $V_j^\nu$ , where  $\|\phi_{i, j, k}\|_{L^2(\mathbb{R}^2)}^2 = \frac{1}{4}$ ,  $i = 0, \dots, 15; j \in \mathbb{Z}; k \in \mathbb{Z}^2$ .
- $\{V_j^\nu\}_{j \in \mathbb{Z}}$  themselves already form a multiresolution of  $L^2(\mathbb{R}^2)$ .



Consider the subspaces  $W_j^0$ ,  $W_j^1$ ,  $W_j^2$ , and  $W_j^3$  of  $W_j$  in the same manner, i.e.,

$$W_j^\nu := \text{clos}_{L^2(\mathbb{R}^2)} \text{span} \{ \psi_{2^\nu, j, k}^r, \psi_{2^{\nu+1}, j, k}^r, \psi_{2^{\nu+8}, j, k}^r, \psi_{2^{\nu+9}, j, k}^r : r = 1, 2, 3; k \in \mathbb{Z}^2 \}.$$

- The generating functions form an orthogonal basis of  $W_j^\nu$ ,  $\nu = 0, 1, 2, 3$ , where  $\|\psi_{i, j, k}^r\|_{L^2(\mathbb{R}^2)}^2 = \frac{1}{4}$ ,  $i = 0, \dots, 15; j \in \mathbb{Z}; k \in \mathbb{Z}^2, r = 1, 2, 3$ .
- $W_j^\nu \perp V_j^\nu$

## Tight wavelet frame

Each generating function set

$$\Psi^\nu := \{\psi_{2^\nu,j,k}^r, \psi_{2^{\nu+1},j,k}^r, \psi_{2^{\nu+8},j,k}^r, \psi_{2^{\nu+9},j,k}^r : r = 1, 2, 3; j \in \mathbb{Z}; k \in \mathbb{Z}^2\}, \quad \nu = 0, 1, 2, 3,$$

forms an orthogonal basis of  $L^2(\mathbb{R}^2)$  with

$$\|f\|_{L^2(\mathbb{R}^2)}^2 = \sum_{\psi \in \Psi^\nu} \frac{|\langle f, \psi \rangle|^2}{\langle \psi, \psi \rangle} = 4 \sum_{\psi \in \Psi^\nu} |\langle f, \psi \rangle|^2 \quad \forall f \in L^2(\mathbb{R}^2), \nu = 0, 1, 2, 3.$$

The set of directional Haar wavelets

$$\Psi_{DH} := \{\psi_{i,j,k}^r : i = 0, \dots, 15; r = 1, 2, 3; j \in \mathbb{Z}; k \in \mathbb{Z}^2\} = \bigcup_{\nu=0}^3 \Psi^\nu$$

forms a Parseval frame of  $L^2(\mathbb{R}^2)$  with

$$\|f\|_{L^2(\mathbb{R}^2)}^2 = \sum_{\psi \in \Psi_{DH}} |\langle f, \psi \rangle|^2 \quad \forall f \in L^2(\mathbb{R}^2).$$

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## Redundance relations

The family of functions  $\{\phi_i(\cdot - k) : i = 0, \dots, 15; k \in \mathbb{Z}^2\}$  generates a frame of  $V_0$ . We have the following dependencies:

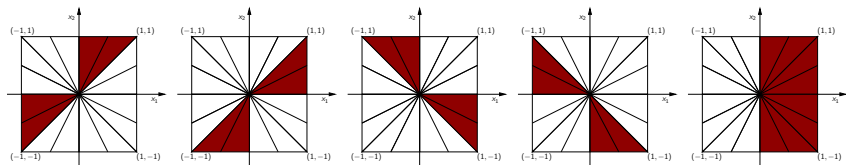
$$\phi_0 + \phi_1 = \phi_{10}(\cdot - \begin{pmatrix} 1 \\ 1 \end{pmatrix}) + \phi_{11}(\cdot - \begin{pmatrix} 1 \\ 1 \end{pmatrix}),$$

$$\phi_2 + \phi_3 = \phi_8(\cdot - \begin{pmatrix} 1 \\ 1 \end{pmatrix}) + \phi_9(\cdot - \begin{pmatrix} 1 \\ 1 \end{pmatrix}),$$

$$\phi_4 + \phi_5 = \phi_{14}(\cdot - \begin{pmatrix} 1 \\ -1 \end{pmatrix}) + \phi_{15}(\cdot - \begin{pmatrix} 1 \\ -1 \end{pmatrix}),$$

$$\phi_6 + \phi_7 = \phi_{12}(\cdot - \begin{pmatrix} 1 \\ -1 \end{pmatrix}) + \phi_{13}(\cdot - \begin{pmatrix} 1 \\ -1 \end{pmatrix}),$$

$$\phi_0 + \phi_1 + \phi_2 + \phi_3 = \phi_4(\cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}) + \phi_5(\cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}) + \phi_6(\cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}) + \phi_7(\cdot - \begin{pmatrix} 0 \\ 1 \end{pmatrix}).$$



$\implies$  In every  $2 \times 2$ -block of a digital image we have 20 redundance equations.

$\implies$  Collect these 20 equations into a matrix  $U \in \mathbb{R}^{20 \times 64}$  such that  $U\Phi_0 = 0$ .

## Directional filter bank algorithm

- Input: Initial image in  $V_0$ :

$$f = \sum_{k \in J} f_{0,k}^T \Phi_0(\cdot - k), \quad f_{0,k} = \langle f, \tilde{\Phi}_0(\cdot - k) \rangle$$

- Add redundancies in  $V_0$ :

$$f = \sum_{k \in J} (f_{0,k}^T + d_k^T U) \Phi_0(\cdot - k)$$

- Decomposition into  $V_{-1} \oplus W_{-1}$  by  $A \Phi_0 = \Psi_{-1}$

$$f = \sum_{k \in J} (f_{0,k}^T + d_k^T U) A^{-1} \Psi_{-1}(\cdot - k)$$

- For each  $k \in J$  compute  $d_k \in \mathbb{R}^{20}$  such that the  $l^0$ -norm

$$\left\| (f_{0,k}^T + d_k^T U) A^{-1} \right\|_0 = \left\| f_{-1,k}^T + d_k^T U A^{-1} \right\|_0$$

becomes minimal.

- Let  $\tilde{f}_{-1,k}^T$  be this minimized coefficient vector. Compute the sparse representation

$$f = \sum_{k \in J} \tilde{f}_{-1,k}^T \Psi_{-1}(\cdot - k)$$

## Minimization of $l^0$ -norm

Goal:

$$\min_{d_k \in \mathbb{R}^{20}} \left\{ \left\| f_{-1,k}^T + d_k^T UA^{-1} \right\|_0 \right\}$$

Idea: Choose  $d_k \in \mathbb{R}^{20}$  such that  $f_{-1,k}^T + d_k^T UA^{-1}$  contains at least 20 zeros.

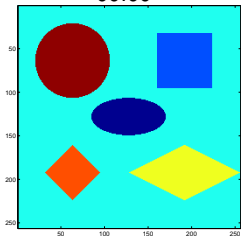
- Compute the orthogonal projections of  $f$  into the subspaces  $V_{-1}^\nu \oplus W_{-1}^\nu$ ,  $\nu = 0, 1, 2, 3$ .
- Consider the corresponding 64 coefficients and select the smallest coefficients first.
- Find  $d_k$  such that these coefficients will be eliminated.

We can prove:

- Our method is optimal for piecewise constant images.
- The resulting sparse representation does not depend on the initial representation of the signal.

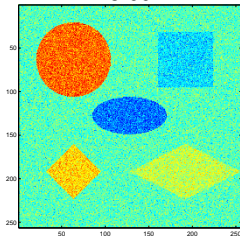
# Denoising of piecewise constant images

00.00



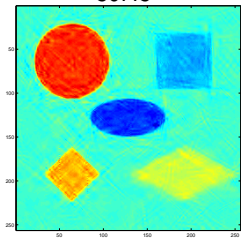
Input image.

23.00



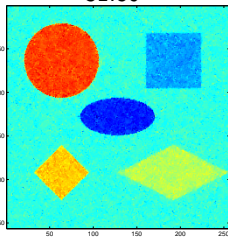
Noisy image ( $\sigma = 20$ ).

30.43



Denoised by contourlets.

31.86



Denoised by our method.



## Future prospects

- Smoother scaling/wavelet functions
- More directions: doubling of directions in each level.
- ...

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Thanks for your attention!