

# Multivariate Anisotropic Periodic Wavelets

Ronny Bergmann

AG Bildverarbeitung  
TU Kaiserslautern

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Erlangen



FELIX KLEIN  
ZENTRUM FÜR  
MATHEMATIK

# Introduction

Periodic wavelets were first defined for the univariate case [PT95]

- based on shifts by  $2\pi/N$ ,  $N \in \mathbb{N}$
- de la Vallée Poussin type wavelets and an FWT [Se98]

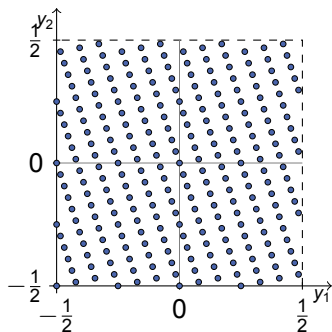
For the multivariate generalization

- based on certain shifts by  $\mathbf{y} \in \mathbb{T}^d := [-\pi, \pi)^d$
  - scaling factor  $j$  replaced by a matrix  $\mathbf{J}$  [MS03]
  - for fixed  $|\det \mathbf{J}| = 2$ : several matrices  $\mathbf{J}$  available [LP10]
- ⇒ preference of direction

## Topics for this talk

- construction of multivariate de la Vallée Poussin type wavelets
- a way to characterize directions

# Pattern and Generating Set



The pattern  $\mathcal{P}(\mathbf{M})$ ,

$$\mathbf{M} = \begin{pmatrix} 28 & -12 \\ 12 & 4 \end{pmatrix}$$

Throughout this talk, let  $\mathbf{M} \in \mathbb{Z}^{d \times d}$  be regular.

- pattern

$$\mathcal{P}(\mathbf{M}) := \left[-\frac{1}{2}, \frac{1}{2}\right)^d \cap \mathbf{M}^{-1}\mathbb{Z}^d$$

- generating set

$$\mathcal{G}(\mathbf{M}) := \mathbf{M}\mathcal{P}(\mathbf{M}) = \mathbf{M}\left[-\frac{1}{2}, \frac{1}{2}\right)^d \cap \mathbb{Z}^d$$

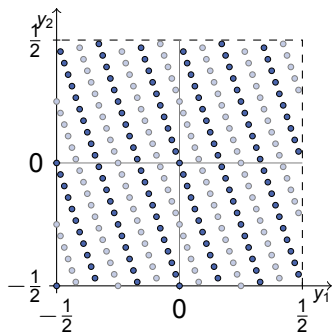
We have

- $m := |\mathcal{P}(\mathbf{M})| = |\mathcal{G}(\mathbf{M})| = |\det \mathbf{M}|$

- the group  $(\mathcal{P}(\mathbf{M}), + \text{ mod } 1)$

- subpatterns  $\mathcal{P}(\mathbf{N})$ , for  
 $\mathbf{M} = \mathbf{JN}$ ,  $\mathbf{J}, \mathbf{N} \in \mathbb{Z}^{d \times d}$

# Pattern and Generating Set



subpattern  $\mathcal{P}(\mathbf{N}) \subset \mathcal{P}(\mathbf{M})$ ,

$$\mathbf{M} = \begin{pmatrix} 28 & -12 \\ 12 & 4 \end{pmatrix} = \mathbf{J}_Y \begin{pmatrix} 28 & -12 \\ 6 & 2 \end{pmatrix}$$

$$\mathbf{J}_Y := \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix}$$

Throughout this talk, let  $\mathbf{M} \in \mathbb{Z}^{d \times d}$  be regular.

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- the group  $(\mathcal{P}(\mathbf{M}), + \text{ mod } 1)$

- subpatterns  $\mathcal{P}(\mathbf{N})$ , for  
 $\mathbf{M} = \mathbf{J}\mathbf{N}$ ,  $\mathbf{J}, \mathbf{N} \in \mathbb{Z}^{d \times d}$

## Fourier Basics

For fixed orderings of  $\mathcal{G}(\mathbf{M}^T)$  and  $\mathcal{P}(\mathbf{M})$ :

- Fourier matrix:  $\mathcal{F}(\mathbf{M}) := \frac{1}{\sqrt{m}} \left( e^{-2\pi i \mathbf{h}^T \mathbf{y}} \right)_{\mathbf{h} \in \mathcal{G}(\mathbf{M}^T), \mathbf{y} \in \mathcal{P}(\mathbf{M})} \in \mathbb{C}^{m \times m}$
- The discrete Fourier transform for  $\mathbf{a} = (\mathbf{a}_y)_{y \in \mathcal{P}(\mathbf{M})} \in \mathbb{C}^m$  is defined as

$$\hat{\mathbf{a}} = (\hat{\mathbf{a}}_{\mathbf{h}})_{\mathbf{h} \in \mathcal{G}(\mathbf{M}^T)} := \sqrt{m} \mathcal{F}(\mathbf{M}) \mathbf{a} \in \mathbb{C}^m.$$

- Fourier coefficients of  $f \in L_2(\mathbb{T}^d)$  are given by

$$c_{\mathbf{k}}(f) := \langle f, e^{i\mathbf{k}^T \circ} \rangle = \frac{1}{(2\pi)^d} \int_{\mathbb{T}^d} f(\mathbf{x}) e^{-i\mathbf{k}^T \mathbf{x}} d\mathbf{x}, \quad \mathbf{k} \in \mathbb{Z}^d.$$

The translation invariant space of  $\xi \in L_2(\mathbb{T}^d)$  w.r.t  $\mathcal{P}(\mathbf{M})$  is given by

- $V_{\mathbf{M}}^{\xi} := \left\{ f; f = \sum_{\mathbf{y} \in \mathcal{P}(\mathbf{M})} \mathbf{a}_{f, \mathbf{y}} \xi(\circ - 2\pi \mathbf{y}), \quad \mathbf{a}_f = (\mathbf{a}_{f, \mathbf{y}})_{\mathbf{y} \in \mathcal{P}(\mathbf{M})} \in \mathbb{C}^m \right\}$
- expressed in Fourier coefficients: For all  $\mathbf{h} \in \mathcal{G}(\mathbf{M}^T)$ ,  $\mathbf{z} \in \mathbb{Z}^d$

$$c_{\mathbf{h} + \mathbf{M}^T \mathbf{z}}(f) = \hat{\mathbf{a}}_{f, \mathbf{h}} c_{\mathbf{h} + \mathbf{M}^T \mathbf{z}}(\xi), \quad \text{where } \hat{\mathbf{a}}_f = \sqrt{m} \mathcal{F}(\mathbf{M}) \mathbf{a}_f.$$

# Wavelet Transform

Factorize  $\mathbf{M} = \mathbf{J}\mathbf{N}$ ,  $|\det \mathbf{J}| = 2$  and take functions  $\xi, \varphi \in L_2(\mathbb{T}^d)$  such that

- $\xi(\circ - 2\pi\mathbf{y})$ ,  $\mathbf{y} \in \mathcal{P}(\mathbf{M})$ , linear independent
  - $\varphi(\circ - 2\pi\mathbf{x})$ ,  $\mathbf{x} \in \mathcal{P}(\mathbf{N})$ , linear independent
  - $\varphi \in V_{\mathbf{M}}^{\xi}$ , i.e.  $V_{\mathbf{N}}^{\varphi} \subset V_{\mathbf{M}}^{\xi}$  and hence  $\dim V_{\mathbf{N}}^{\varphi} = \frac{1}{2} \dim V_{\mathbf{M}}^{\xi} = \frac{m}{2}$
- $\Rightarrow \exists$  wavelet  $\psi \in L_2(\mathbb{T}^d)$  s.t.  $V_{\mathbf{M}}^{\xi} = V_{\mathbf{N}}^{\varphi} \oplus V_{\mathbf{N}}^{\psi}$ .

Decompose  $f \in V_{\mathbf{M}}^{\xi}$  into

$$\begin{aligned} f &= \sum_{\mathbf{y} \in \mathcal{P}(\mathbf{M})} a_{f,\mathbf{y}} \xi(\circ - 2\pi\mathbf{y}) = g + h \\ &= \sum_{\mathbf{x} \in \mathcal{P}(\mathbf{N})} a_{g,\mathbf{x}} \varphi(\circ - 2\pi\mathbf{x}) + \sum_{\mathbf{x} \in \mathcal{P}(\mathbf{N})} a_{h,\mathbf{x}} \psi(\circ - 2\pi\mathbf{x}) \end{aligned}$$

$\hat{\mathbf{a}}_g, \hat{\mathbf{a}}_h \in \mathbb{C}^{\frac{m}{2}}$  are computed using only  $\hat{\mathbf{a}}_f$ ,  $\hat{\mathbf{a}}_{\varphi}$ , and  $\hat{\mathbf{a}}_{\psi}$ .

$\Rightarrow$  **Fast wavelet transform (B., 2013)**

## Constructing Wavelets

We construct wavelets by their Fourier coefficients. We choose

- a nonnegative function  $g : \mathbb{R}^d \rightarrow \mathbb{R}_+$  with

$$\sum_{\mathbf{z} \in \mathbb{Z}^d} g(\mathbf{x} + \mathbf{z}) = 1 \quad \text{and} \quad g(\mathbf{x}) > 0, \quad \text{for all } \mathbf{x} \in \left[-\frac{1}{2}, \frac{1}{2}\right)^d$$

- matrices  $\mathbf{J}_1, \dots, \mathbf{J}_n, \mathbf{M}_0 \in \mathbb{Z}^{d \times d}$ ,  $|\det \mathbf{J}_l| = 2$

And define

- matrices  $\mathbf{M}_l := \mathbf{J}_l \dots \mathbf{J}_1 \mathbf{M}_0$ ,  $m_l := 2^l |\det \mathbf{M}_0|$
- matrix vectors  $\mathcal{J}_{l,k} := (\mathbf{J}_l, \dots, \mathbf{J}_k)$ ,

$$\mathbf{B}_{\mathcal{J}_{l,n}}(\mathbf{x}) := \begin{cases} g(\mathbf{x}) & l = n + 1 \\ \left( \sum_{\mathbf{z} \in \mathbb{Z}^d} g(\mathbf{x} + \mathbf{J}_l^T \mathbf{z}) \right) \mathbf{B}_{\mathcal{J}_{l+1,n}}(\mathbf{J}_l^{-T} \mathbf{x}) & l = n, n-1, \dots, 1 \end{cases}$$

$$\tilde{\mathbf{B}}_{\mathcal{J}_{l,n}}(\mathbf{x}) := e^{-2\pi i \mathbf{x}^T \mathbf{w}_l} \left( \sum_{\mathbf{z} \in \mathbb{Z}^d} g(\mathbf{x} + \mathbf{J}_l^T \mathbf{z} - \mathbf{v}_l) \right) \mathbf{B}_{\mathcal{J}_{l+1,n}}(\mathbf{J}_l^{-T} \mathbf{x}), \quad l \leq n,$$

where  $\mathbf{v}_l \in \mathcal{P}(\mathbf{J}_l^T) \setminus \{\mathbf{0}\}$  and  $\mathbf{w}_l \in \mathcal{P}(\mathbf{J}_l) \setminus \{\mathbf{0}\}$  (both unique)

# Constructing Wavelets II

The Multivariate Wavelets of de la Vallée Poussin Type

## Definition

Define scaling functions  $\varphi_{\mathbf{M}_l}^{\mathcal{J}_{l+1,n}}$  and wavelets  $\psi_{\mathbf{M}_l}^{\mathcal{J}_{l+1,n}}$  of de la Vallée Poussin type in Fourier coefficients

$$\mathbf{c}_{\mathbf{k}}(\varphi_{\mathbf{M}_l}^{\mathcal{J}_{l+1,n}}) := \frac{1}{\sqrt{m_l}} B_{\mathcal{J}_{l+1,n}}(\mathbf{M}_l^{-\mathbf{T}} \mathbf{k}), \quad \mathbf{k} \in \mathbb{Z}^d, \quad l = 0, \dots, n$$

$$\mathbf{c}_{\mathbf{k}}(\psi_{\mathbf{M}_l}^{\mathcal{J}_{l+1,n}}) := \frac{1}{\sqrt{m_l}} \tilde{B}_{\mathcal{J}_{l+1,n}}(\mathbf{M}_l^{-\mathbf{T}} \mathbf{k}), \quad \mathbf{k} \in \mathbb{Z}^d, \quad l = 0, \dots, n-1.$$

## Remark

If  $g$  is smooth, then  $B_{\mathcal{J}_{l,n}}$  is smooth

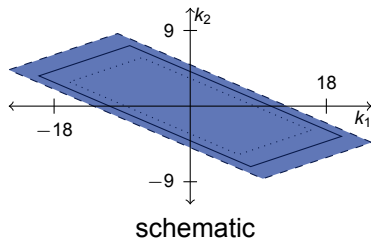
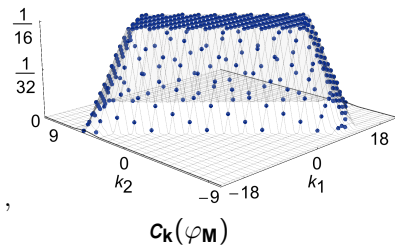
$\mathbf{c}_{\mathbf{k}}(\varphi_{\mathbf{M}_l}^{\mathcal{J}_{l+1,n}})$  and  $\mathbf{c}_{\mathbf{k}}(\psi_{\mathbf{M}_l}^{\mathcal{J}_{l+1,n}})$  are samples obtained from a smooth function  
 $\Rightarrow$  localization



# Example of a Wavelet

De la Vallée Poussin-type scaling functions and wavelets

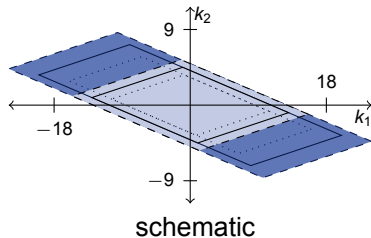
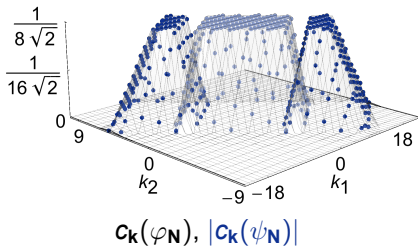
- Let  $g$  be the Box spline with  $\Xi = \begin{pmatrix} 1 & 0 & \frac{1}{10} & 0 \\ 0 & 1 & 0 & \frac{1}{10} \end{pmatrix}$
- $\mathbf{M} = \begin{pmatrix} 28 & -12 \\ 12 & 4 \end{pmatrix} = \mathbf{J}_X \begin{pmatrix} 14 & -6 \\ 12 & 4 \end{pmatrix}$ ,  $\mathbf{J}_X = \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}$
- $\mathbf{c}_k(\varphi_{\mathbf{M}}) = \mathbf{g}(\mathbf{M}^{-\mathbf{T}}\mathbf{k})$ ,  $\mathbf{c}_k(\varphi_{\mathbf{N}}^{(\mathbf{J}_X)}) = \mathbf{c}_k(\varphi_{\mathbf{N}}) = \mathbf{g}(\mathbf{N}^{-\mathbf{T}}\mathbf{k})$



# Example of a Wavelet

De la Vallée Poussin-type scaling functions and wavelets

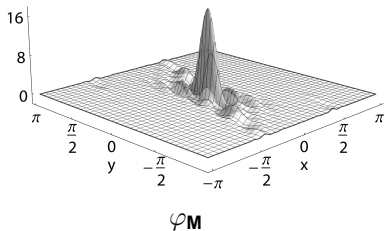
- Let  $g$  be the Box spline with  $\Xi = \begin{pmatrix} 1 & 0 & \frac{1}{10} & 0 \\ 0 & 1 & 0 & \frac{1}{10} \end{pmatrix}$
- $\mathbf{M} = \begin{pmatrix} 28 & -12 \\ 12 & 4 \end{pmatrix} = \mathbf{J}_X \begin{pmatrix} 14 & -6 \\ 12 & 4 \end{pmatrix}$ ,  $\mathbf{J}_X = \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}$
- $\mathbf{c}_k(\varphi_{\mathbf{M}}) = \mathbf{g}(\mathbf{M}^{-T}\mathbf{k})$ ,  $\mathbf{c}_k(\varphi_{\mathbf{N}}^{(\mathbf{J}_X)}) = \mathbf{c}_k(\varphi_{\mathbf{N}}) = \mathbf{g}(\mathbf{N}^{-T}\mathbf{k})$



# Example of a Wavelet

De la Vallée Poussin-type scaling functions and wavelets

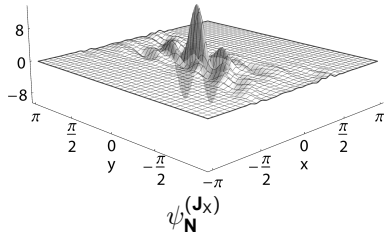
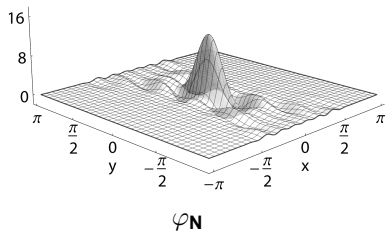
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- $\mathbf{c}_k(\varphi_{\mathbf{M}}) = \mathbf{g}(\mathbf{M}^{-\mathbf{T}}\mathbf{k})$ ,  $\mathbf{c}_k(\varphi_{\mathbf{N}}^{(\mathbf{J}_X)}) = \mathbf{c}_k(\varphi_{\mathbf{N}}) = \mathbf{g}(\mathbf{N}^{-\mathbf{T}}\mathbf{k})$



# Example of a Wavelet

De la Vallée Poussin-type scaling functions and wavelets

- Let  $g$  be the Box spline with  $\Xi = \begin{pmatrix} 1 & 0 & \frac{1}{10} & 0 \\ 0 & 1 & 0 & \frac{1}{10} \end{pmatrix}$
- $\mathbf{M} = \begin{pmatrix} 28 & -12 \\ 12 & 4 \end{pmatrix} = \mathbf{J}_X \begin{pmatrix} 14 & -6 \\ 12 & 4 \end{pmatrix}$ ,  $\mathbf{J}_X = \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}$
- $c_{\mathbf{k}}(\varphi_{\mathbf{M}}) = g(\mathbf{M}^{-T}\mathbf{k})$ ,  $c_{\mathbf{k}}(\varphi_{\mathbf{N}}^{(\mathbf{J}_X)}) = c_{\mathbf{k}}(\varphi_{\mathbf{N}}) = g(\mathbf{N}^{-T}\mathbf{k})$



# Properties of the de la Vallée Poussin Type Wavelets

## Theorem (B., J. Prestin, 2014)

For  $l = 0, \dots, n - 1$

- 1  $\varphi_{\mathbf{M}_l}^{\mathcal{J}_{l+1},n} \in \text{span} \left\{ \varphi_{\mathbf{M}_{l+1}}^{\mathcal{J}_{l+2},n}(\circ - 2\pi\mathbf{y}) ; \mathbf{y} \in \mathcal{P}(\mathbf{M}_{l+1}) \right\} =: V_{l+1}$
- 2  $\dim V_{l+1} = |\det \mathbf{M}_{l+1}|$
- 3  $V_{l+1} = V_l \oplus \text{span} \left\{ \psi_{\mathbf{M}_l}^{\mathcal{J}_{l+1},n}(\circ - 2\pi\mathbf{y}) ; \mathbf{y} \in \mathcal{P}(\mathbf{M}_l) \right\}.$

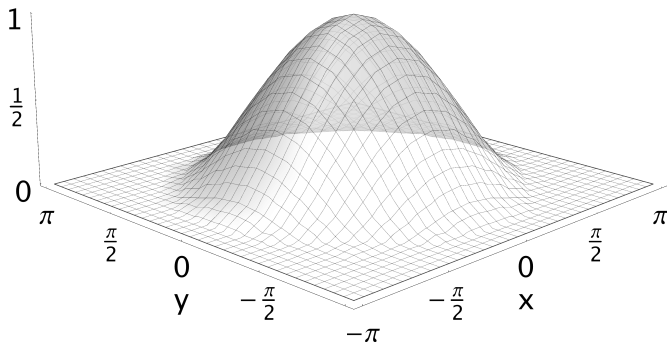
With slight restriction on  $\mathbf{g} \Rightarrow \psi_{\mathbf{M}_l}^{\mathcal{J}_{l+1},n} = \psi_{\mathbf{M}_l}^{(\mathbf{J}_{l+1})}$  and  $\varphi_{\mathbf{M}_l}^{\mathcal{J}_{l+1},n} = \varphi_{\mathbf{M}_l}^{(\mathbf{J}_{l+1})}.$

$\Rightarrow$  With an infinite sequence  $\{\mathbf{J}_k\}_{k \in \mathbb{N}}, |\det \mathbf{J}_k| = 2,$

the sequence of spaces  $\{V_l\}_{l \in \mathbb{N}}$  forms an **MRA**.

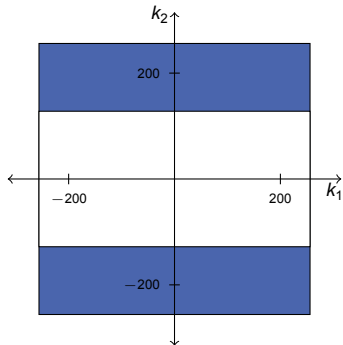
## Example of a Decomposition

- radial function based on a piecewise quadratic function
- jump in second directional derivative on a circle
- sampling with  $\mathbf{M} = 512 \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \Rightarrow 512 \times 512$  pixel image.

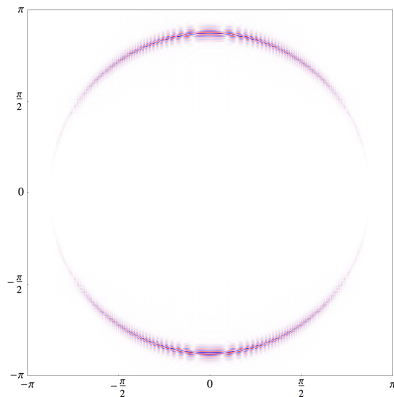


## Example of a Decomposition

$$\mathbf{M} = \mathbf{J}_Y \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_X \mathbf{N}_{1234567}$$



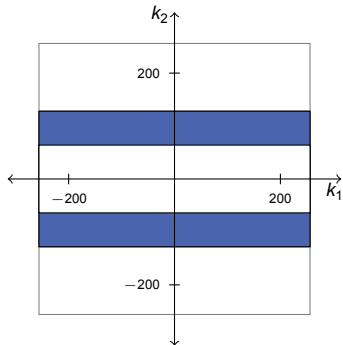
Wavelet  $\psi_{\mathbf{N}_{1234567}}^{(\mathbf{J}_Y \mathbf{J}_X)}$ ,  $\mathbf{N}_1 = \begin{pmatrix} 512 & 0 \\ 0 & 256 \end{pmatrix}$



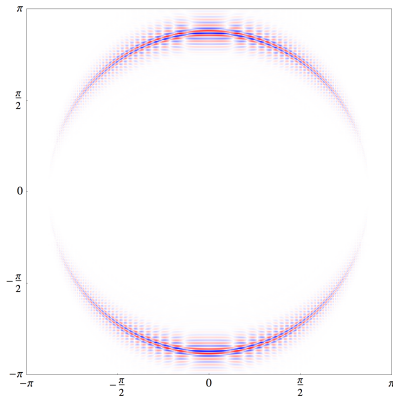
Corresp. wavelet part

## Example of a Decomposition

$$\mathbf{M} = \mathbf{J}_Y \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_X \mathbf{N}_{1234567}$$



Wavelet  $\psi_{\mathbf{N}_{1234567}}^{(\mathbf{J}_Y \mathbf{J}_X)}$ ,  $\mathbf{N}_2 = \begin{pmatrix} 512 & 0 \\ 0 & 128 \end{pmatrix}$

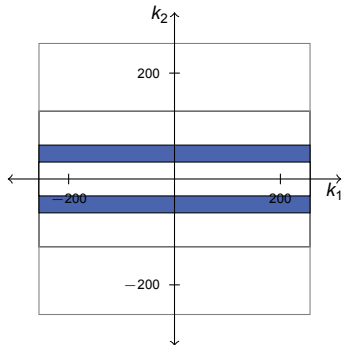


Corresp. wavelet part

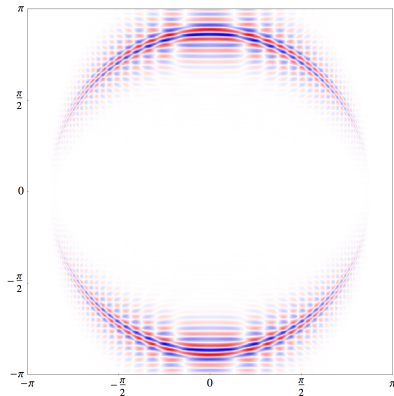


## Example of a Decomposition

$$\mathbf{M} = \mathbf{J}_Y \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_X \mathbf{N}_{1234567}$$



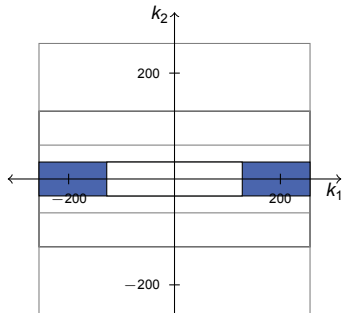
Wavelet  $\psi_{\mathbf{N}_{1234567}}^{(\mathbf{J}_Y \mathbf{J}_X)}$ ,  $\mathbf{N}_3 = \begin{pmatrix} 512 & 0 \\ 0 & 64 \end{pmatrix}$



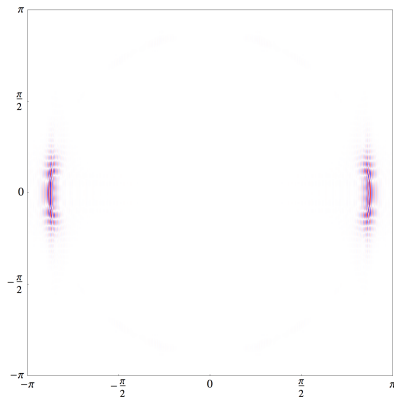
Corresp. wavelet part

## Example of a Decomposition

$$\mathbf{M} = \mathbf{J}_Y \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_X \mathbf{N}_{1234567}$$



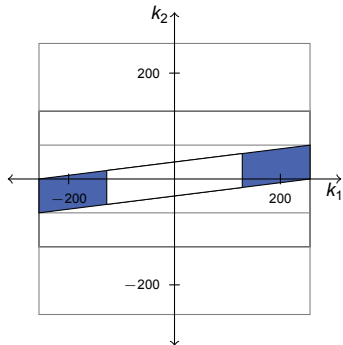
Wavelet  $\psi_{\mathbf{N}_{1234567}}^{(\mathbf{J}_Y \mathbf{J}_X)}$ ,  $\mathbf{N}_4 = \begin{pmatrix} 256 & 0 \\ 0 & 64 \end{pmatrix}$



Corresp. wavelet part

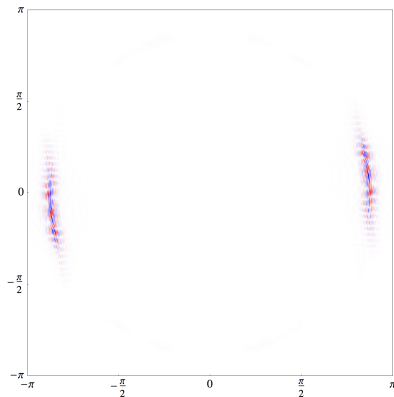
## Example of a Decomposition

$$\mathbf{M} = \mathbf{J}_Y \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_X \mathbf{N}_{1234567}$$



Wavelet  $\psi_{\mathbf{N}_{1234567}}^{(\mathbf{J}_Y \mathbf{J}_X)}$ ,  $\mathbf{N}_5 = \begin{pmatrix} 256 & 32 \\ 0 & 64 \end{pmatrix}$

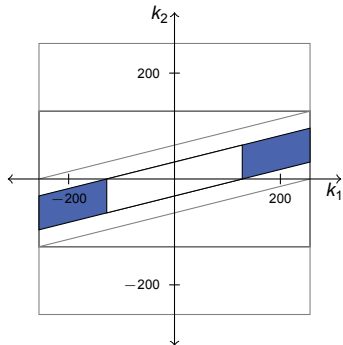
$$\mathbf{J}_{Y-} := \begin{pmatrix} 1 & -1 \\ 0 & 2 \end{pmatrix}$$



Corresp. wavelet part

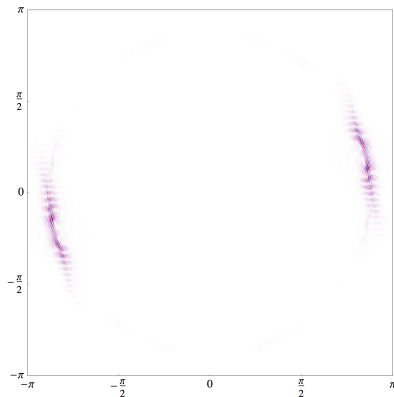
## Example of a Decomposition

$$\mathbf{M} = \mathbf{J}_Y \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_X \mathbf{N}_{1234567}$$



Wavelet  $\psi_{\mathbf{N}_{1234567}}^{(\mathbf{J}_Y \mathbf{J}_X)}$ ,  $\mathbf{N}_6 = \begin{pmatrix} 256 & 64 \\ 0 & 64 \end{pmatrix}$

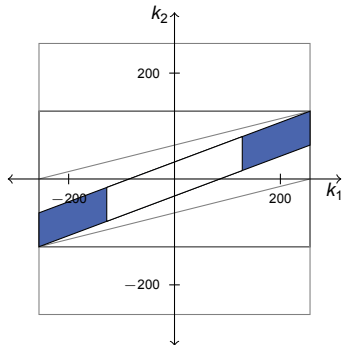
$$\mathbf{J}_{Y-} := \begin{pmatrix} 1 & -1 \\ 0 & 2 \end{pmatrix}$$



Corresp. wavelet part

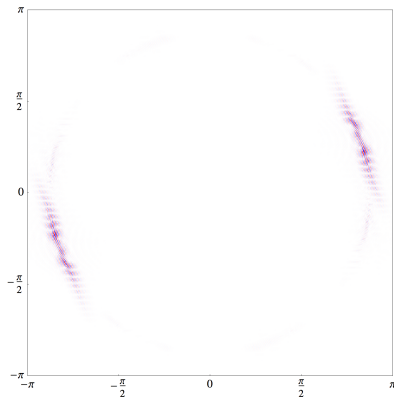
## Example of a Decomposition

$$\mathbf{M} = \mathbf{J}_Y \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_Y \mathbf{J}_Y - \mathbf{J}_X \mathbf{N}_{1234567}$$



Wavelet  $\psi_{\mathbf{N}_{1234567}}^{(\mathbf{J}_Y \mathbf{J}_X)}$ ,  $\mathbf{N}_7 = \begin{pmatrix} 256 & 96 \\ 0 & 64 \end{pmatrix}$

$$\mathbf{J}_{Y-} := \begin{pmatrix} 1 & -1 \\ 0 & 2 \end{pmatrix}$$



Corresp. wavelet part

numbering: binary in matrices and directly in multiples of 32 in shear

## Conclusion

Patterns  $\mathcal{P}(\mathbf{M})$  and generating sets  $\mathcal{G}(\mathbf{M}^T)$

- generalize equally spaced points
- still resemble an FFT
- fast wavelet transform based with corresponding TI spaces

The constructed wavelets generalize the onedimensional  
*de la Vallée Poussin wavelets*

- to arbitrary dyadic scaling matrices
  - based on arbitrary smooth functions  $g$
- ⇒ localization
- for many functions  $g$  we have an MRA

Taking several finite sequences of matrices  $\mathbf{J}_l$   
⇒ dictionary of directional wavelets

# Literature

B., J. Prestin, *Multivariate periodic wavelets of de la Vallée Poussin type*, Preprint, [arxiv.org/pdf/1402.3710v1.pdf](https://arxiv.org/pdf/1402.3710v1.pdf).

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Thank you for your attention.