

FAST FRAMELET TRANSFORMS ON MANIFOLDS

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MCQMC, Stanford, 2016

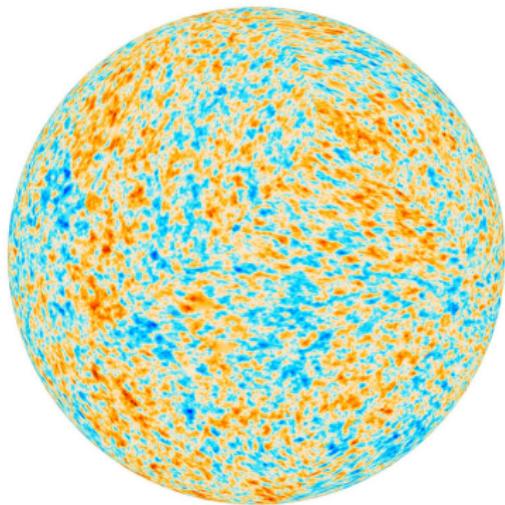
Joint with Xiaosheng Zhuang

Handwriting

"What win I if I gain the thing
I seek...
A thought, A breath
A froth of fleeting joy...
Who buys a minutes mirth
To wait a week.
Or sells eternity, for a toy

- 26 letters (values)
- Pixels $512 \times 512 = 262,144$
- Locate on 2-d torus

CMB data



- Collected by Planck observer
- Contains 12,582,912 data
- Sampled from 2-d sphere

High-dimensional data on low-dimensional manifold

These examples which have a large number of data, or **high-dimensional data**, but sampled from a **low-dimensional structure** widely exist.

Manifolds: sphere, torus, surface, meshes ...

High-dimensional data on low-dimensional manifold

These examples which have a large number of data, or high-dimensional data, but sampled from a low-dimensional structure widely exist.

Manifolds: sphere, torus, surface, meshes ...

How to efficiently represent such data?

How to do data processing, e.g. inpainting an image, classifying medical information and apply to disease diagnosis?

Manifolds

- Compact and Smooth Riemannian Manifold \mathcal{M}
- $\dim \mathcal{M} \geq 2$, $\mu(\mathcal{M}) = 1$
- eigenvalues λ_ℓ and eigenfunctions u_ℓ satisfy

$$\Delta u_\ell = -\lambda_\ell^2 u_\ell, \quad \ell = 0, 1, \dots$$

$$0 = \lambda_0 \leq \lambda_1 \leq \lambda_2 < \dots$$

Representation using localised frame?

- Assuming the function f of **data** is in $L_2(\mathcal{M}, \mu)$.
- In data representation, the **localised frame** plays a similar role as the **delta function** in \mathbb{R} .

$$f * \delta = f.$$

Filters

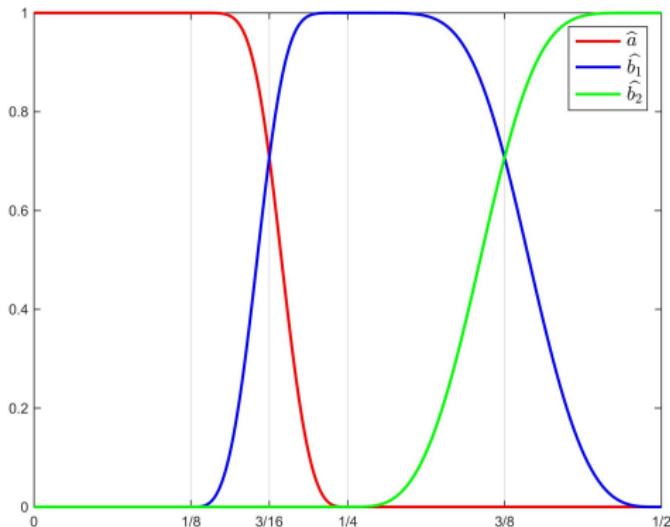


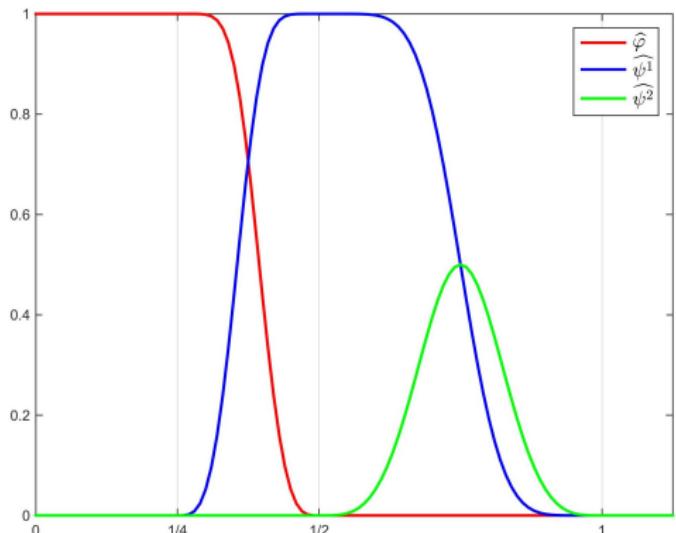
Fig. Filters $\hat{a}, \hat{b}_1, \hat{b}_2 \in C^3(\mathbb{R})$

- $a, b_1, b_2 \in \ell_2(\mathbb{Z})$

- $\hat{a}, \hat{b}_1, \hat{b}_2 \in \mathbb{L}_2(\mathbb{R})$

$$\hat{a}(\xi) := \sum_{j \in \mathbb{Z}} a(j) e^{-2\pi i j \xi}$$

Refinable and wavelet functions



For $\xi \in \mathbb{R}$

- $\widehat{\alpha}(2\xi) = \widehat{a}(\xi)\widehat{\alpha}(\xi)$
- $\widehat{\beta^1}(2\xi) = \widehat{b}_1(\xi)\widehat{\alpha}(\xi)$
- $\widehat{\beta^2}(2\xi) = \widehat{b}_2(\xi)\widehat{\alpha}(\xi)$
- $\widehat{\alpha}, \widehat{\beta^1}, \widehat{\beta^2} \in L_2(\mathbb{R})$

Fig. Meyer refinable and wavelet functions
 $\widehat{\alpha}, \widehat{\beta^1}, \widehat{\beta^2} \in C^3(\mathbb{R})$

Continuous framelets

See e.g. Maggioni, Mhaskar 2008, Hammond et al., 2011 & Dong., 2015.

Continuous framelets are **filtered** expansions of **eigenfunctions** on \mathcal{M} .

For $j \in \mathbb{Z}$ and $x, y \in \mathcal{M}$,

$$\varphi_{j,y}(x) := \sum_{\ell=0}^{\infty} \widehat{\alpha} \left(\frac{\lambda_\ell}{2^j} \right) \overline{u_\ell}(y) u_\ell(x) \quad (\text{low-pass})$$

$$\psi_{j,y}^1(x) := \sum_{\ell=0}^{\infty} \widehat{\beta^1} \left(\frac{\lambda_\ell}{2^j} \right) \overline{u_\ell}(y) u_\ell(x) \quad (\text{high-pass})$$

$$\psi_{j,y}^2(x) := \sum_{\ell=0}^{\infty} \widehat{\beta^2} \left(\frac{\lambda_\ell}{2^j} \right) \overline{u_\ell}(y) u_\ell(x) \quad (\text{high-pass}).$$

How to construct discrete frame on manifold?

For \mathbb{R}^d , translation at integer grids,

$$\int_{\mathbb{R}^d} \langle f, \psi_{j,y} \rangle \psi_{j,y} dy \approx \sum_{y \in \mathbb{Z}^d} \langle f, \psi_{j,y} \rangle \psi_{j,y}$$

How to construct analogue to framelets on \mathbb{R}^d ?

For \mathbb{R}^d , translation at integer grids,

$$\int_{\mathbb{R}^d} \langle f, \psi_{j,y} \rangle \psi_{j,y} dy dy \approx \sum_{y \in \mathbb{Z}^d} \langle f, \psi_{j,y} \rangle \psi_{j,y}$$

For \mathcal{M} , translation at quadrature nodes,

$$\int_{\mathcal{M}} \langle f, \psi_{j,y} \rangle \psi_{j,y} d\mu(y) \approx \sum_{y \in \Lambda_j(\mathcal{M})} w_{j,y} \langle f, \psi_{j,y} \rangle \psi_{j,y}$$

$\{(w_{j,y}, y) | y \in \Lambda_j(\mathcal{M})\}$ is a quadrature rule on \mathcal{M}

Framelet quadrature rules on \mathcal{M}

For $j \geq 0$, the framelet quadrature rule for scaling level j is

$$\mathcal{Q}_{N_j} := \{(\omega_{j,k}, x_{j,k}) | \omega_{j,k} > 0, k = 1, \dots, N_j\},$$

is a set of pairs of weights and points on \mathcal{M} .

e.g. Brandolini, Gigante, Travaglini et al., 2014.

Framelets on \mathcal{M}

Framelets are **filtered** expansions of **eigenfunctions** associated with **framelet quadrature rules** on \mathcal{M} .

For $j \in \mathbb{Z}$ and $\mathbf{x}, \mathbf{y} \in \mathcal{M}$,

$$\varphi_{j,k}(\mathbf{x}) := \sqrt{\omega_{j,k}} \sum_{\ell=0}^{\infty} \widehat{\alpha} \left(\frac{\lambda_\ell}{2^j} \right) \overline{u_\ell}(\mathbf{x}_{j,k}) u_\ell(\mathbf{x}) \quad (\text{low-pass})$$

$$\psi_{j,k}^1(\mathbf{x}) := \sqrt{\omega_{j,k}} \sum_{\ell=0}^{\infty} \widehat{\beta^1} \left(\frac{\lambda_\ell}{2^j} \right) \overline{u_\ell}(\mathbf{x}_{j,k}) u_\ell(\mathbf{x}) \quad (\text{high-pass})$$

$$\psi_{j,k}^2(\mathbf{x}) := \sqrt{\omega_{j,k}} \sum_{\ell=0}^{\infty} \widehat{\beta^2} \left(\frac{\lambda_\ell}{2^j} \right) \overline{u_\ell}(\mathbf{x}_{j,k}) u_\ell(\mathbf{x}) \quad (\text{high-pass}).$$

Framelet system

For $J \in \mathbb{Z}$, let

$$\text{FS}_J := \{\varphi_{J,k} | k = 1, \dots, N_J\} \cup \{\psi_{j,k}^1, \psi_{j,k}^2 | k = 1, \dots, N_j, j \geq J\}.$$

When are framelet systems tight?

Theorem (Tightness of FS_J)

Let $\dim \mathcal{M} \geq 2$. Assume that the supports of $\widehat{\alpha}$, $\widehat{\beta^n}$, $n = 1, \dots, r$, are subsets of $[0, 1]$. Let $J_0 \in \mathbb{Z}$. Then, the following statements are equivalent.

- (i) For any $J \geq J_0$, FS_J is a **tight frame**, i.e. for $f \in L_2(\mathcal{M})$,

$$\|f\|_{L_2(\mathcal{M})}^2 = \sum_{k=1}^{N_J} |\langle f, \varphi_{J,k} \rangle|^2 + \sum_{n=1}^r \sum_{j=J}^{\infty} \sum_{k=1}^{N_j} |\langle f, \psi_{j,k}^n \rangle|^2.$$

- (ii) For $f \in L_2(\mathcal{M})$,

$$\lim_{j \rightarrow \infty} \left\| \sum_{k=1}^{N_j} \langle f, \varphi_{j,k} \rangle \varphi_{j,k} - f \right\|_{L_2(\mathcal{M})} = 0,$$

$$\begin{aligned} & \sum_{j=1}^{N_{j+1}} \langle f, \varphi_{j+1,k} \rangle \varphi_{j+1,k} \\ &= \sum_{j=1}^{N_j} \langle f, \varphi_{j,y} \rangle \varphi_{j,k} + \sum_{n=1}^r \sum_{j=1}^{N_j} \langle f, \psi_{j,k}^n \rangle \psi_{j,k}^n, \quad j \geq J_0. \end{aligned}$$

When are framelet systems tight?

Theorem (Continued)

Let $\dim \mathcal{M} \geq 2$. Assume that the supports of $\widehat{\alpha}, \widehat{\beta}$ are subsets of $[0, 1]$. Let $J_0 \in \mathbb{Z}$. Then, the each below is equivalent to the above.

(iii) The scaling functions and quadrature rules satisfy

$$\lim_{j \rightarrow \infty} \bar{\widehat{\alpha}}\left(\frac{\lambda_\ell}{2^j}\right) \widehat{\alpha}\left(\frac{\lambda_{\ell'}}{2^j}\right) \mathcal{U}_{\ell, \ell'}(\mathcal{Q}_{N_j}) = \delta_{\ell, \ell'},$$

$$\bar{\widehat{\alpha}}\left(\frac{\lambda_\ell}{2^{j+1}}\right) \widehat{\alpha}\left(\frac{\lambda_{\ell'}}{2^{j+1}}\right) \mathcal{U}_{\ell, \ell'}(\mathcal{Q}_{N_{j+1}}) = \left[\bar{\widehat{\alpha}}\left(\frac{\lambda_\ell}{2^j}\right) \widehat{\alpha}\left(\frac{\lambda_{\ell'}}{2^j}\right) + \sum_{n=1}^r \bar{\widehat{\beta}}^n\left(\frac{\lambda_\ell}{2^j}\right) \widehat{\beta}^n\left(\frac{\lambda_{\ell'}}{2^j}\right) \right] \mathcal{U}_{\ell, \ell'}(\mathcal{Q}_{N_j})$$

for all $\ell, \ell' \geq 0$ and $j \geq J_0$, where

$$\mathcal{U}_{\ell, \ell'}(\mathcal{Q}_{N_j}) := \sum_{k=1}^{N_j} \omega_{j,k} u_\ell(\mathbf{x}_{j,k}) \overline{u_{\ell'}(\mathbf{x}_{j,k})}.$$

Quadrature rule exact for polynomials on \mathcal{M}

For $n \geq 0$, let $\Pi_n := \text{span}\{\underline{u}_\ell | \lambda_\ell \leq n\}$.

For $j \geq 0$, the **framelet quadrature rule** for scaling level j is

$$\mathcal{Q}_{N_j} := \{(\omega_{j,k}, \underline{x}_{j,k}) | \omega_{j,k} > 0, k = 1, \dots, N_j\},$$

exact for polynomials of degree up to $c \cdot 2^j - 1$.

$$\left(\int_{\mathcal{M}} q(\underline{x}) d\mu(\underline{x}) = \sum_{k=1}^{N_j} \omega_{j,k} q(\underline{x}_{j,k}), \quad q \in \Pi_{c \cdot 2^j - 1} \right)$$

Then (iii) \iff

(iii)' The **refinable** and **wavelet** functions satisfy

$$\left| \widehat{\alpha} \left(\frac{\lambda_\ell}{2^{j+1}} \right) \right|^2 = \left| \widehat{\alpha} \left(\frac{\lambda_\ell}{2^j} \right) \right|^2 + \sum_{n=1}^r \left| \widehat{\beta^n} \left(\frac{\lambda_\ell}{2^j} \right) \right|^2.$$

E.g. Meyer wavelets satisfy this.

Fast evaluation

Given a set of data $(\textcolor{green}{f}(\textcolor{brown}{x}_1), \dots, \textcolor{green}{f}(\textcolor{brown}{x}_N))$ on \mathcal{M} , how to **fast** and **effectively** evaluate the framelet representation, or the **framelet coefficients**?

$$\|f\|_{L_2(\mathcal{M})}^2 = \sum_{k=1}^{N_J} |\langle \textcolor{green}{f}, \varphi_{J,k} \rangle|^2 + \sum_{n=1}^r \sum_{j=J}^{\infty} \sum_{k=1}^{N_j} |\langle \textcolor{green}{f}, \psi_{j,k}^n \rangle|^2.$$

How to **efficiently** evaluate function values at **other points**?

Fast evaluation by FMT

Given a set of data $(\textcolor{green}{f}(\textcolor{brown}{x}_1), \dots, \textcolor{green}{f}(\textcolor{brown}{x}_N))$ on \mathcal{M} , how to **fast** and **effectively** evaluate the framelet representation, or the **framelet coefficients**?

$$\|f\|_{L_2(\mathcal{M})}^2 = \sum_{k=1}^{N_J} |\langle \textcolor{green}{f}, \varphi_{J,k} \rangle|^2 + \sum_{n=1}^r \sum_{j=J}^{\infty} \sum_{k=1}^{N_j} |\langle \textcolor{green}{f}, \psi_{j,k}^n \rangle|^2.$$

- **Decomposition**

How to **efficiently** evaluate function values at **other points**?

- **Reconstruction**

Framelet coefficients

For $k = 1, \dots, N_j$, let

$$v_{j,k} := \langle f, \varphi_{j,k} \rangle$$

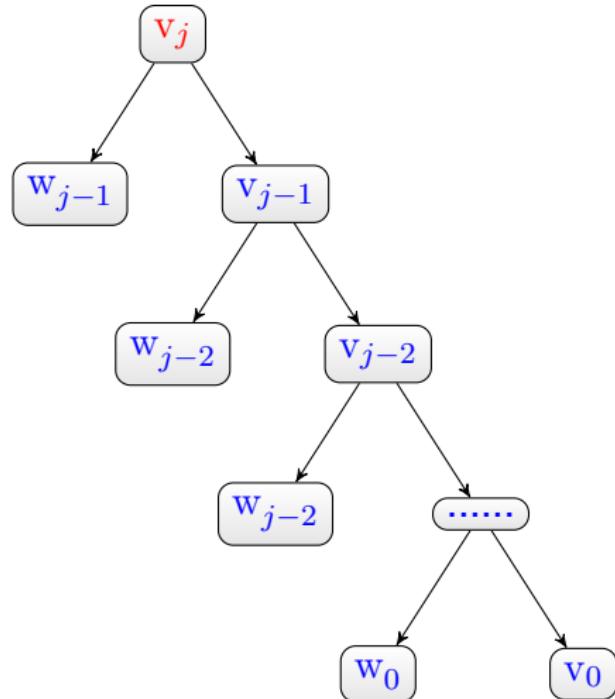
$$w_{j,k} := \langle f, \psi_{j,k} \rangle$$

and

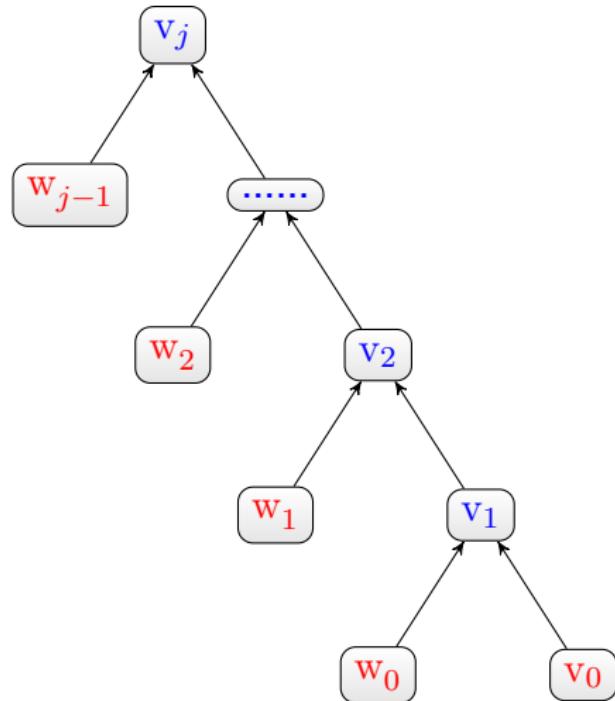
$$\mathbf{v}_j := (v_{j,1}, \dots, v_{j,N_j}) \approx (f(\mathbf{x}_{j,1}), \dots, f(\mathbf{x}_{j,N_j}))$$

$$\mathbf{w}_j := (w_{j,1}, \dots, w_{j,N_j}).$$

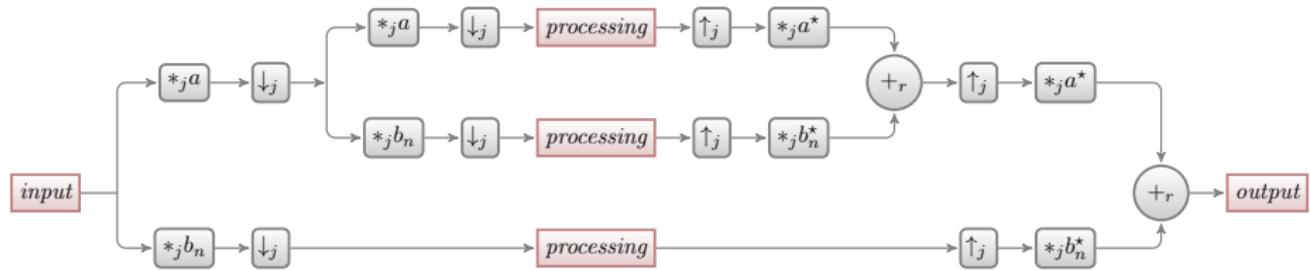
Decomposition



Reconstruction



Filter Bank for framelet transforms



Decomposition via Transition operator

Theorem

Let $\dim \mathcal{M} \geq 2$ and \mathcal{M} be a smooth and compact R. MFD.

$$\mathbf{v}_{j-1} = \mathbf{T}_a \mathbf{v}_j = (\mathbf{v}_j *_j a^*) \downarrow_j, \quad \mathbf{w}_{j-1}^n = \mathbf{T}_{b_n} \mathbf{v}_j = (\mathbf{v}_j *_j b_n^*) \downarrow_j.$$

For $k = 1, \dots, N_{j-1}$,

$$v_{j-1,k} = \sum_{\lambda_\ell \leq 2^{j-1}} \widehat{v}_{j,\ell} \bar{\widehat{a}}\left(\frac{\lambda_\ell}{2^j}\right) u_\ell(x_{j-1,k})$$

$$w_{j-1,k}^n = \sum_{\lambda_\ell \leq 2^{j-1}} \widehat{v}_{j,\ell} \bar{\widehat{b}_n}\left(\frac{\lambda_\ell}{2^j}\right) u_\ell(x_{j-1,k}).$$

Discrete Fourier transforms

Let $l(\mathcal{Q}_{N_j})$ be the set of sequences $\mathbf{v} : [1, N_j] \cap \mathbb{N} \rightarrow \mathbb{C}$ supported on $[1, N_j] \cap \mathbb{N}$. Define $\Lambda_j := \{\ell \in \mathbb{N}_0 : \lambda_\ell \leq 2^{j-1}\}$ and $l(\Lambda_j)$ be the set of sequences supported on Λ_j .

For $j, j' \in \mathbb{Z}$, the **discrete Fourier transform (DFT)** $\mathbf{F}_{j,j'} : l(\Lambda_j) \rightarrow l(\mathcal{Q}_{N_{j'}})$ for a sequence $\widehat{\mathbf{v}} = \{\widehat{v}_\ell\}_{\ell \in \Lambda_j} \in l(\Lambda_j)$ is defined to be

$$[\mathbf{F}_{j,j'} \widehat{\mathbf{v}}](k) := \sum_{\lambda_\ell \leq 2^{j-1}} \widehat{v}_\ell \sqrt{\omega_{j',k}} u_\ell(\mathbf{x}_{j',k}), \quad k = 1, \dots, N_{j'}.$$

The **adjoint discrete Fourier transform** $\mathbf{F}_{j',j}^* : l(\mathcal{Q}_{N_{j'}}) \rightarrow l(\Lambda_j)$ is

$$(\mathbf{F}_{j',j}^* \mathbf{v})_\ell := \sum_{k=1}^{N_{j'}} \mathbf{v}(k) \sqrt{\omega_{j',k}} \overline{u_\ell}(\mathbf{x}_{j',k}), \quad \ell \in \Lambda_j.$$

Decomposition via DFT

Theorem

Let $\dim \mathcal{M} \geq 2$ and \mathcal{M} be a smooth and compact R. MFD.

$$v_{j-1} = F_{j,j-1}(v_j *_j a^*), \quad w_{j-1}^n = F_{j,j-1}(v_j *_j b_n^*).$$

Algorithm 1: Decomposition in Multi-Level FMT

Input : v_J
Output: $(w_{J-1}, w_{J-2}, \dots, w_0; v_0)$

- 1 $v_J \rightarrow \hat{v}_J$; // inverse FFT
- 2 **for** $j \leftarrow J$ **to** 1 **do**
- 3 $\hat{v}_{j-1} \leftarrow (\hat{v}_j) \downarrow_j \bar{\hat{a}}(2^{-j} \lambda.)$; // dwsmp & conv
- 4 $\hat{w}_{j-1}^n \leftarrow (\hat{v}_j) \downarrow_j \bar{\hat{b}}_n(2^{-j} \lambda.)$; // dwsmp & conv
- 5 $w_{j-1}^n \leftarrow \hat{w}_{j-1}^n$; // adjoint FFT
- 6 **end**
- 7 $v_0 \leftarrow \hat{v}_0$; // adjoint FFT

Assume FFT on \mathcal{M} : $\mathcal{O}(N(\log N)^m)$, $m > 0$.

Total complexity: $\mathcal{O}(N(\log N)^m)$.

Reconstruction via Subdivision operator

The subdivision operator $\mathbf{S}_h := \mathbf{S}_{h,j} : l(\mathcal{Q}_{N_{j-1}}) \rightarrow l(\Lambda_j, \mathcal{Q}_{N_j})$ is

$$\begin{aligned}\mathbf{S}_h \mathbf{v} &:= (\mathbf{v} \uparrow_j) *_j h \\ &= \mathbf{F}_{j-1,j}^*(\mathbf{v}) *_j h \quad (h = a, b).\end{aligned}$$

Theorem

Let $\dim \mathcal{M} \geq 2$ and \mathcal{M} be a smooth and compact R. MFD.

$$\mathbf{v}_j = \mathbf{S}_a \mathbf{v}_{j-1} + \sum_{n=1}^r \mathbf{S}_{b_n} \mathbf{w}_{j-1}^n.$$

Fast framelet transform algorithm — Reconstruction

Algorithm 2: Reconstruction in Multi-Level FMT

Input : $(w_{J-1}, w_{J-2}, \dots, w_0; v_0)$
Output: v_J

```
1  $(v_0)^\dagger \leftarrow v_0;$  // adjoint FFT
2  $(w_0)^\dagger \leftarrow w_0;$  // adjoint FFT
3 for  $j \leftarrow 1$  to  $J$  do
4    $(v_j)^\dagger \leftarrow ((\hat{v}_{j-1})\uparrow_j)^\dagger \cdot \hat{a}(2^{-j}\lambda.) + ((\hat{w}_{j-1})\uparrow_j)^\dagger \cdot \hat{b}(2^{-j}\lambda.);$ 
5   // upsmp & conv
6 end
7  $v_J \leftarrow (v_J)^\dagger;$  // adjoint FFT
```

Assume FFT on \mathcal{M} : $\mathcal{O}(N(\log N)^m)$, $m > 0$.

Total complexity: $\mathcal{O}(N(\log N)^m)$.

Example: FMT on \mathbb{S}^2



- $u_\ell = Y_{\ell,m}$
- $\lambda_\ell = \sqrt{\ell(\ell + 1)}$
- \mathcal{Q}_{N_j} = G.-L. tensor, HEALPix
- filters: Meyer, a, b_1, b_2

NFSFT on \mathcal{M} : $\mathcal{O}(N\sqrt{\log N})$
e.g. Keiner, Kunis, Potts., 2007.

G.-L. tensor rule for \mathcal{Q}_{N_j} : $N \sim 2^{2j+1}$
Hesse, Womersley., 2012.

FMT : $\mathcal{O}(N\sqrt{\log N})$

Framelets on \mathbb{S}^2

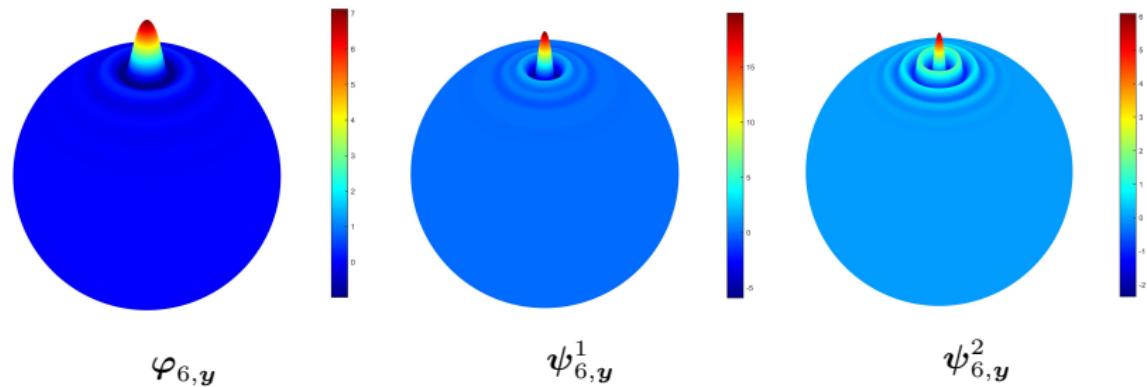
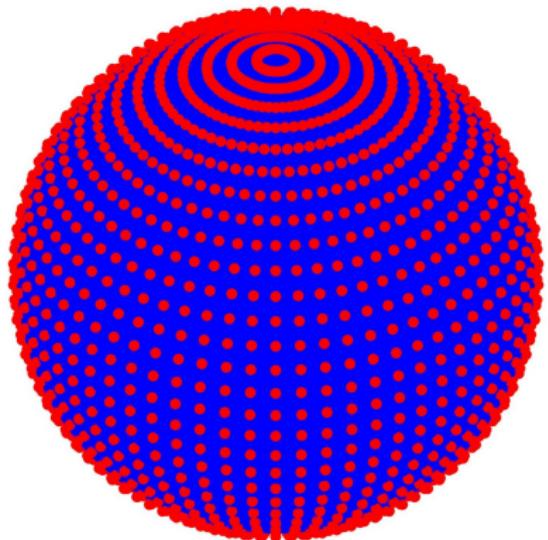


Fig. Framelets on \mathbb{S}^2 , scaling level $j = 6$, dilation at $y = (0, 0, 1)$

Gauss-Legendre tensor rule for framelets $\psi_{j,k}$, $j = 5$

Fig. G-L tensor product rule for degree 63



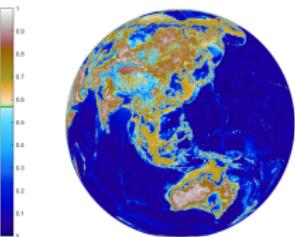
- Non-equal weights
- Nodes $x_{j,k} \in \mathbb{S}^2$, $k = 1, \dots, 2048$.
- Exact for degree $\leq 2^{5+1} - 1 = 63$

e.g. Hesse, Womersley., 2012.

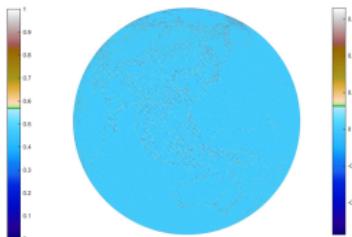
Topographic map on \mathbb{S}^2 , finest level 9, nodes.no $\leq 523,776$



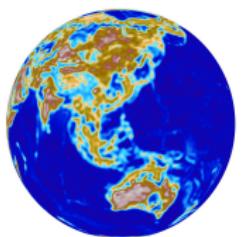
f_{tpg}



v_9



w_9



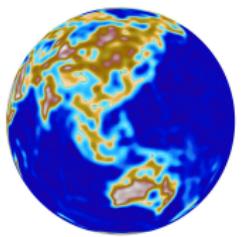
v_8



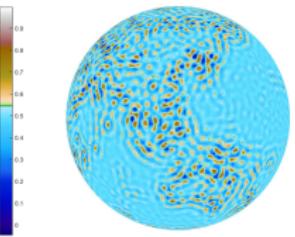
w_8^1



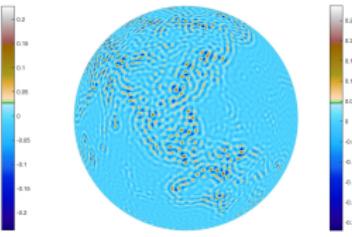
w_8^2



v_7



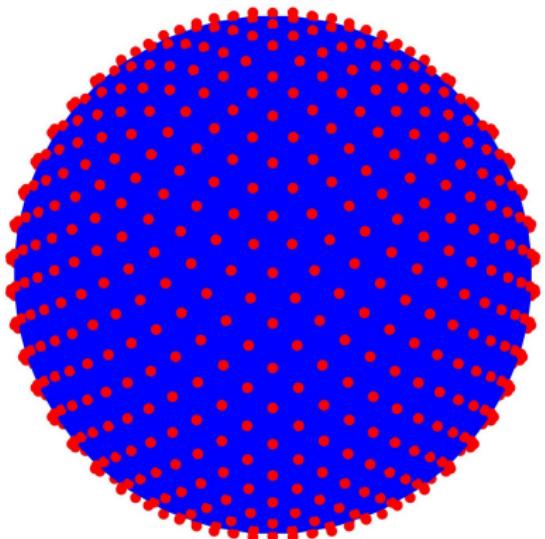
w_7^1



w_7^2

HEALPix points for framelets $\psi_{j,k}$, $j = 4$

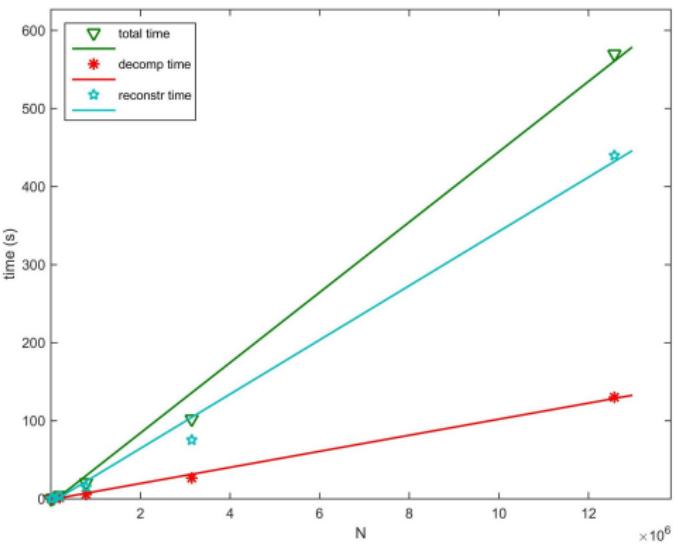
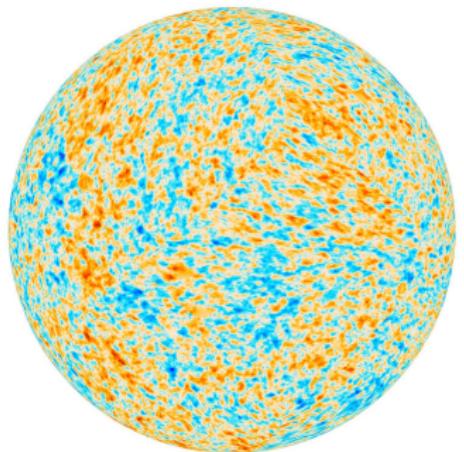
Fig. HL points $N = 768$



- Equal area
- Nested
- NOT polynomial exact

Górski *et al.*, 2005.

CPU time for CMB data, finest level 10, nodes.no $\leq 12,582,912$



Intel Core i7 CPU @ 3.4GHz with 32GB RAM in OS X

References



Y. G. Wang and X. Zhuang.

Tight framelets and fast framelet transforms on manifolds. *submitted*, 2016.



Y. G. Wang, Q. T. Le Gia, I. H. Sloan and R. S. Womersley.

Fully discrete needlet approximation on the sphere. *Appl. Comput. Harmon. Anal.*, 2016.

The End

Thank you!