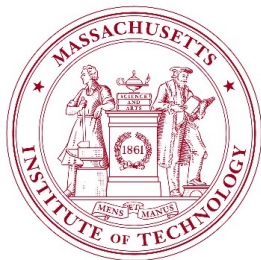


A fast analysis-based discrete Hankel transform using asymptotic expansions

Alex Townsend
MIT



IMA Leslie Fox Prize Meeting, 22nd June, 2015

Based on: T., "A fast analysis-based discrete Hankel transform using asymptotic expansions", to appear in SINUM.

Introduction

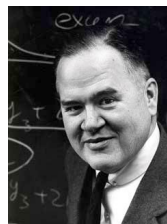
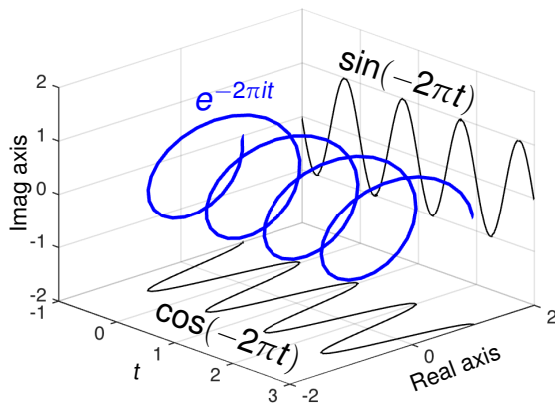
The fast Fourier transform

The FFT computes the DFT in $O(N \log N)$ operations:

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-2\pi i n k / N}, \quad 0 \leq k \leq N-1.$$



James Cooley



John Tukey

Introduction

A circularly symmetric 2D Fourier transform

Let $f(x, y)$ be a circularly symmetric function. Then, the finite Hankel transform is

$$H_0(\omega) = \frac{1}{2\pi} \iint_{x^2+y^2 \leq 1} f(x, y) e^{-i(\omega_1 x + \omega_2 y)} dx dy = \int_0^1 f(r) J_0(r\omega) r dr, \quad \omega^2 = \omega_1^2 + \omega_2^2$$

Discrete analogue: $H_0(j_{0,k}) \approx \frac{1}{j_{0,N+1}^2} \sum_{n=1}^N \frac{2}{J_1^2(j_{0,n})} f(j_{0,n}/j_{0,N+1}) J_0(j_{0,k} j_{0,n}/j_{0,N+1})$.

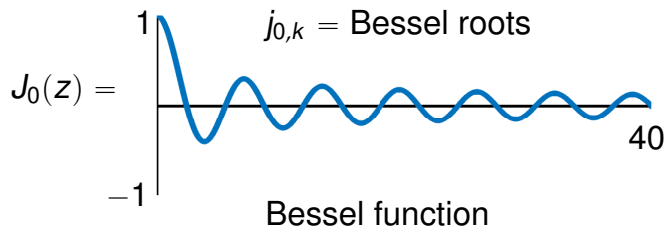
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H. Fisk Johnson

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Independently rediscovered by [Yu et al., 89] and [Guizar-Sicairos & Gutiérrez-Vega, 04].

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H. Fisk Johnson

Introduction

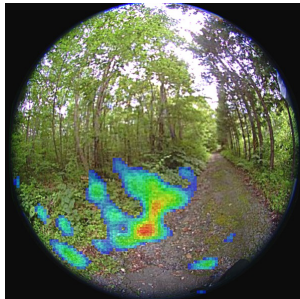
Many applications

Optics, electromagnetics, imaging, and the numerical solution of PDEs:

[Siegman, 77], [Oppenheim, 78], [Nachamkin & Maggiore, 80], [Candel, 81], [Gopalan & Chen, 83], [Johnson, 86], [Johnson, 87], [Higgins & Munson, 88], [Yu et al., 89], [Vittorio et al., 92], [Sharafeddin et al., 92], [Agnesi et al., 93], [Zhao & Halling, 93], [Cree & Bones, 94], [Barakat, 96], [Ferrari, 99], [Secada, 99], [Wieder, 99], [Knockaert, 00], [Zhang et al., 02], [Markham & Conchello, 03], [Perciante & Ferrari, 04], [Guizar-Sicairos & Gutiérrez-Vega, 04], [Cerjan, 07], [Poularikas, 10]

Compton camera:

- Hankel transform is useful for image reconstruction [Cree & Bones, 94].
- Used in nuclear medical imaging and radioactive waste detection.



Introduction

Two existing methods

1. “Direct” approach:

Naively computes

$$\underline{X} = \mathbf{J}_0(\underline{l}_0 \underline{l}_0^T / j_{0,N+1}) \underline{X}$$

in $O(N^2)$ operations [Amos, 86].

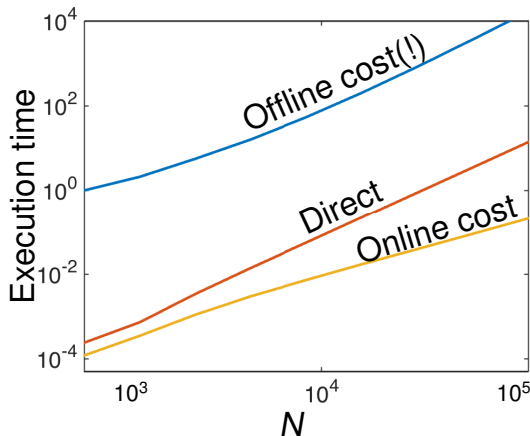
2. Butterfly scheme:

Online cost = $O(N \log N)$

Offline cost = $O(N^2)$

[O’Neil, Woolfe, & Rokhlin, 10].

Butterfly scheme (state-of-the-art)



Timings from [O’Neil, Woolfe, & Rokhlin, 10].

Introduction

Three challenging differences between the DFT and DHT

The discrete Hankel transform of order 0 (DHT) [Johnson, 86]:

$$\underline{X} = \mathbf{J}_0(j_0 j_0^T / j_{0,N+1}) \underline{x}.$$

1. Kernel. $J_0(z)$ does **not** have constant amplitude.
2. Frequencies. $j_{0,1}, \dots, j_{0,N}$ are **not** equispaced.
3. Time samples. $j_{0,1}/j_{0,N+1}, \dots, j_{0,N}/j_{0,N+1}$ are **not** equispaced.

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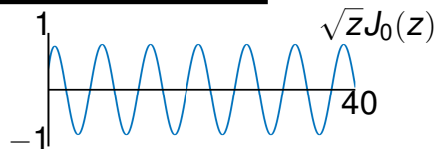
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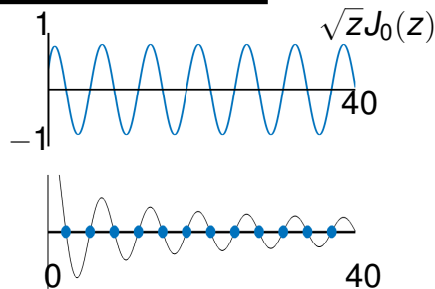
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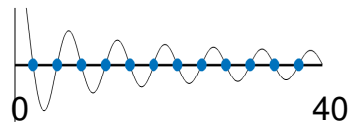
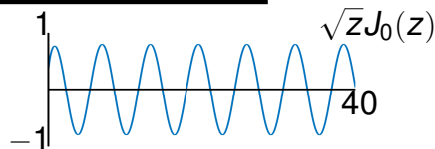
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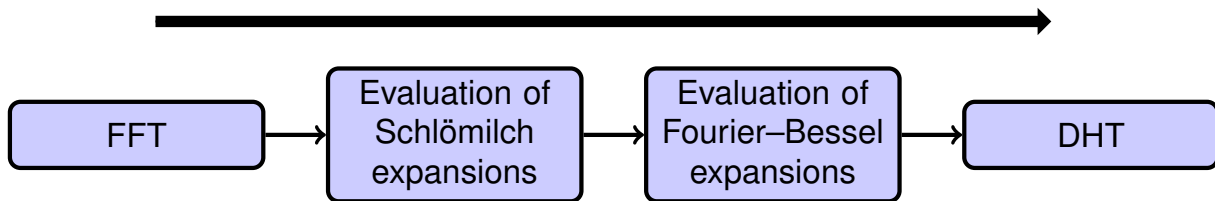

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Introduction

Overview of talk

Increasingly nonuniform



DFT

$$\mathbf{J}_0(\underline{r} \underline{\omega}^T)$$

$$\mathbf{J}_0(\underline{r} \underline{j}_0^T)$$

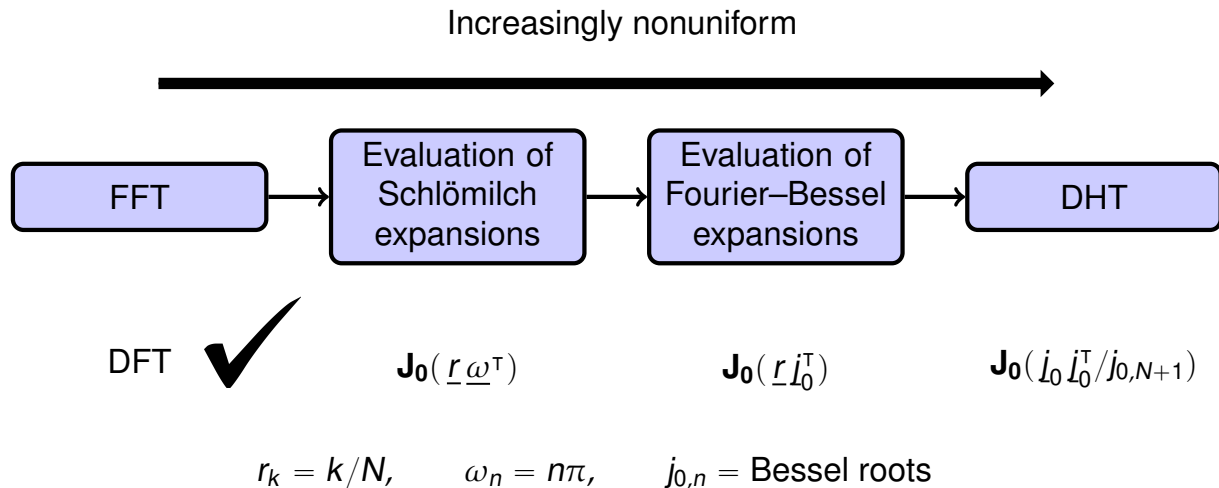
$$\mathbf{J}_0(\underline{j}_0 \underline{j}_0^T / j_{0,N+1})$$

$$r_k = k/N, \quad \omega_n = n\pi, \quad j_{0,n} = \text{Bessel roots.}$$

Goal: FFT-based and analysis-based fast transforms with zero offline cost.

Introduction

Overview of talk



Goal: FFT-based and analysis-based fast transforms with zero offline cost.

Fast evaluation of Schlömilch expansions

Setup

Schlömilch expansion of $f : [0, 1] \rightarrow \mathbb{C}$ is [Schlömilch, 1846]:

$$f(r) = \sum_{n=1}^N x_n J_0(n\pi r).$$



Oscar Schlömilch

Aim: A fast algorithm for evaluating $f(r)$ at $r_k = k/N$ for $1 \leq k \leq N$.

Equivalent to the following matrix-vector product:

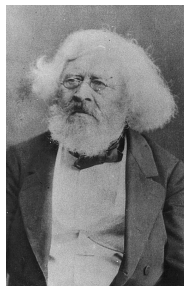
$$\mathbf{J}_0(\underline{r}\underline{\omega}^T)\underline{x} = \begin{pmatrix} J_0(r_1\omega_1) & \dots & J_0(r_1\omega_N) \\ \vdots & \ddots & \vdots \\ J_0(r_N\omega_1) & \dots & J_0(r_N\omega_N) \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix}, \quad r_k = k/N, \quad \omega_n = n\pi.$$

Fast evaluation of Schlömilch expansions

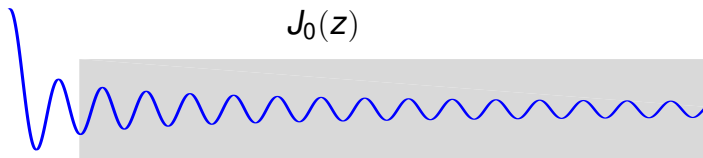
Bessel functions are trigonometric-like for large argument

For fixed $M \geq 1$ and real $z \rightarrow \infty$:

$$J_0(z) \sim \sqrt{\frac{2}{\pi z}} \left(\cos\left(z - \frac{\pi}{4}\right) \sum_{m=0}^{M-1} \frac{(-1)^m a_{2m}}{z^{2m}} - \sin\left(z - \frac{\pi}{4}\right) \sum_{m=0}^{M-1} \frac{(-1)^m a_{2m+1}}{z^{2m+1}} \right).$$



Peter A. Hansen



Fraunhofer regime



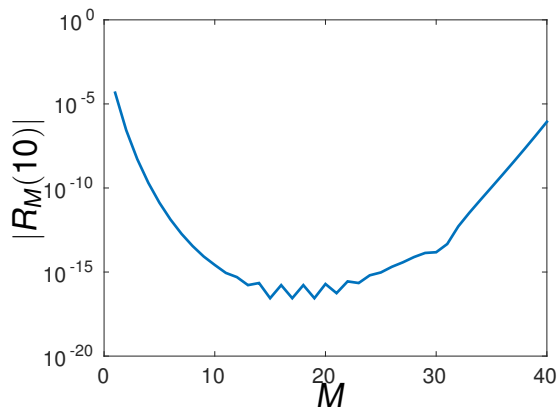
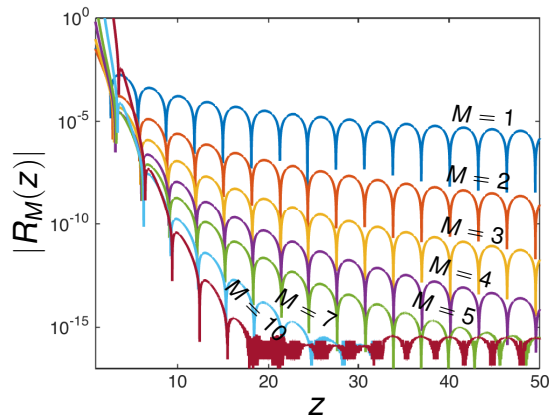
Hermann Hankel

A 19th century hobby: [Poisson, 1823], [Kummer, 1837], [Jacobi, 1843], [Lipschitz, 1859], [Hamilton, 1907]

Fast evaluation of Schlömilch expansions

Numerical pitfalls of an asymptotic expansionist

$$J_0(z) = \sqrt{\frac{2}{\pi z}} \left(\cos\left(z - \frac{\pi}{4}\right) \sum_{m=0}^{M-1} \frac{(-1)^m a_{2m}}{z^{2m}} - \sin\left(z - \frac{\pi}{4}\right) \sum_{m=0}^{M-1} \frac{(-1)^m a_{2m+1}}{z^{2m+1}} \right) + R_M(z)$$



Fix M . Where is the asymptotic expansion accurate?

Fast evaluation of Schlömilch expansions

Recap

Evaluation of a Schlömilch expansion is equivalent to the following matrix-vector product:

$$\mathbf{J}_0(\underline{r}\underline{\omega}^T)\underline{x} = \begin{pmatrix} J_0(r_1\omega_1) & \dots & J_0(r_1\omega_N) \\ \vdots & \ddots & \vdots \\ J_0(r_N\omega_1) & \dots & J_0(r_N\omega_N) \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix}, \quad r_k = k/N, \quad \omega_n = n\pi.$$

Fast evaluation of Schlömilch expansions

Asymptotic expansions as a matrix decomposition

The asymptotic expansion gives a matrix decomposition:

$$\mathbf{J}_0(r_k \omega_n) = \sqrt{\frac{2}{\pi}} \left(\cos(r_k \omega_n - \frac{\pi}{4}) \sum_{m=0}^{M-1} \frac{(-1)^m a_{2m}}{(r_k \omega_n)^{2m+\frac{1}{2}}} - \sin(r_k \omega_n - \frac{\pi}{4}) \sum_{m=0}^{M-1} \frac{(-1)^m a_{2m+1}}{(r_k \omega_n)^{2m+\frac{3}{2}}} \right) + \mathbf{R}_M(r_k \omega_n)$$

which is a sum of diagonally scaled DCTs and DSTs when $r_k = \frac{k}{N}$ and $\omega_n = n\pi$:

$$\mathbf{J}_0(\underline{r} \underline{\omega}^T) = \sum_{m=0}^{M-1} \left(D_{u_m^1} P^T \mathbf{C}_{N+1} P D_{u_m^2} + D_{v_m^1} \begin{bmatrix} \mathbf{S}_{N-1} & 0 \\ 0 & 0 \end{bmatrix} D_{v_m^2} \right) + \mathbf{R}_M.$$

$$\mathbf{J}_0 = \mathbf{J}_0^{\text{ASY}} + \mathbf{R}_M$$

Fast evaluation of Schlömilch expansions

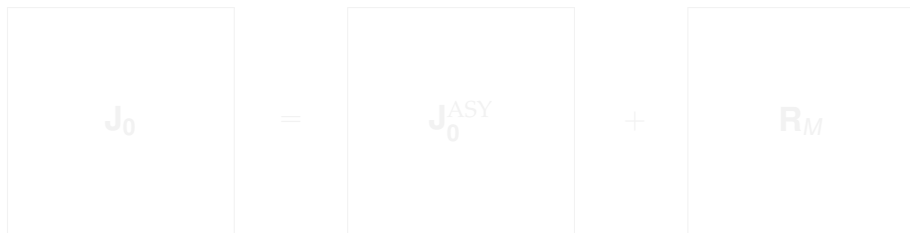
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Fast evaluation of Schlömilch expansions

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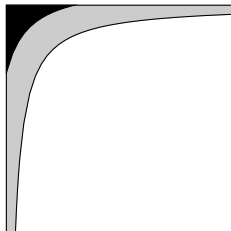
$$\boxed{\mathbf{J}_0} = \boxed{\mathbf{J}_0^{\text{ASY}}} + \boxed{\mathbf{R}_M}$$

Fast evaluation of Schlömilch expansions

Be careful and stay safe

$$\text{Error curve: } |R_M(r_k \omega_n)| = \epsilon$$

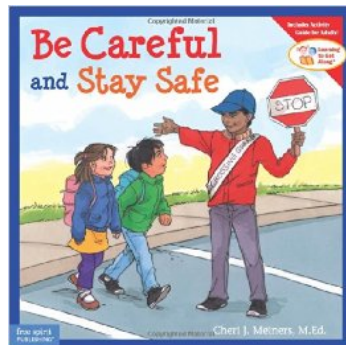
$$R_M(\underline{r} \underline{\omega}^T) =$$



$$nk \leq \frac{N}{\pi} s_{0,M}(\epsilon) \implies |R_M(r_k \omega_n)| < \epsilon$$

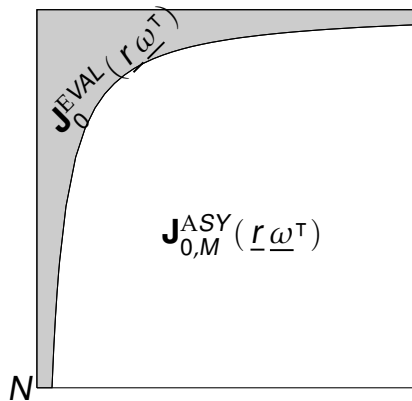
Computed by a
fixed-point iteration

Fix M . Where is the asymptotic expansion accurate?



Fast evaluation of Schlömilch expansions

Partitioning and balancing competing costs



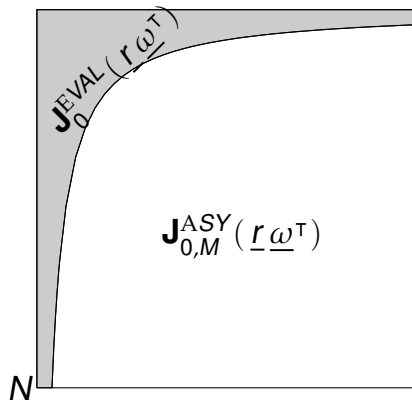
Theorem

The matrix-vector product $\underline{X} = \mathbf{J}_0(\underline{r} \underline{\omega}^T) \underline{x}$ can be computed in $\mathcal{O}(N(\log N)^2 / \log \log N)$ operations.



Fast evaluation of Schlömilch expansions

Partitioning and balancing competing costs



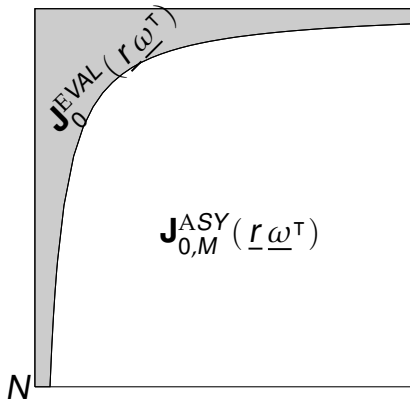
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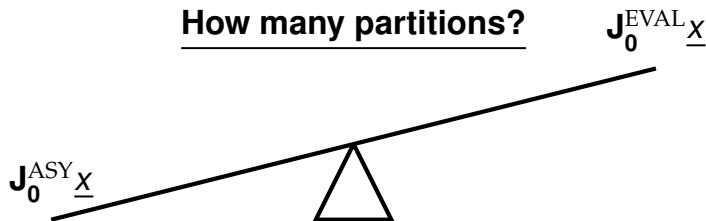
Fast evaluation of Schlömilch expansions

Partitioning and balancing competing costs



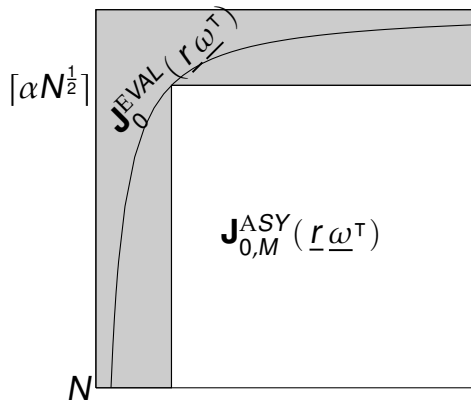
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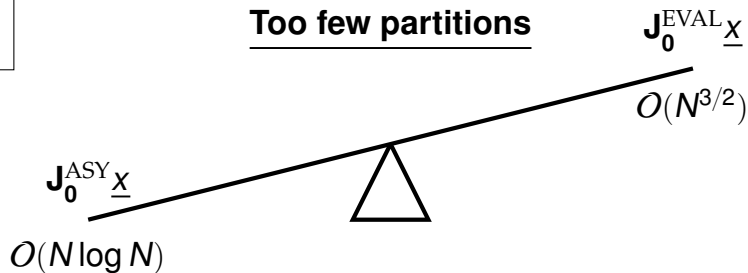
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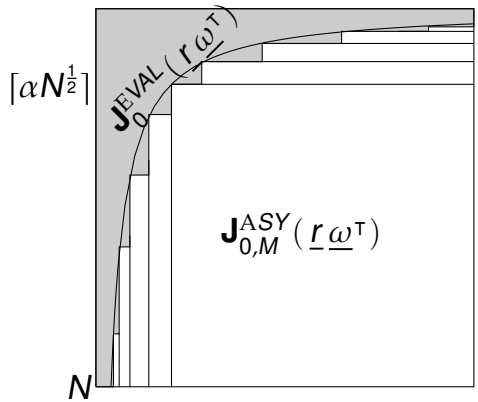
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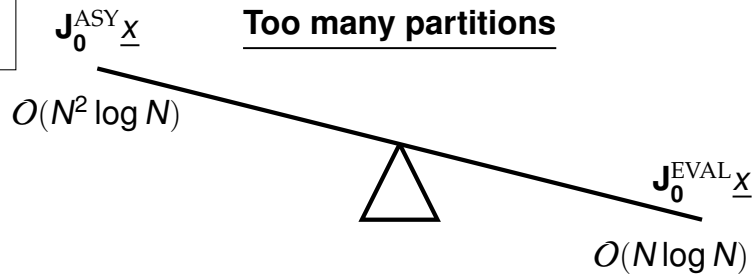
Fast evaluation of Schlömilch expansions

Partitioning and balancing competing costs



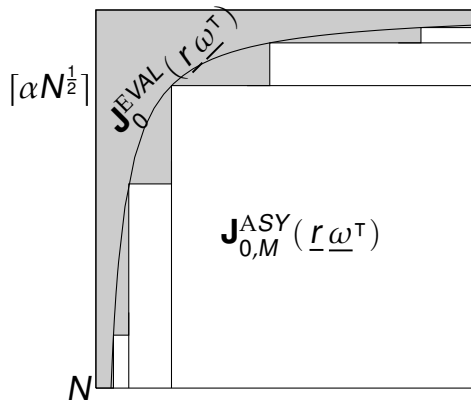
Theorem

The matrix-vector product $\underline{X} = \mathbf{J}_0(\underline{r} \underline{\omega}^T) \underline{x}$ can be computed in $\bar{O}(N(\log N)^2 / \log \log N)$ operations.



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Theorem

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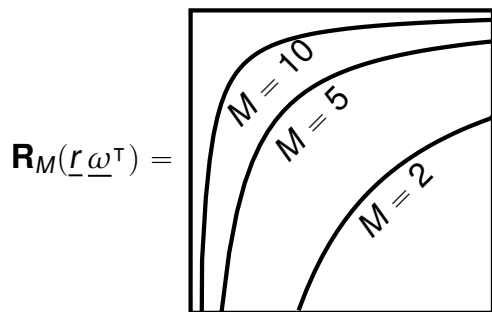
$\mathcal{O}(\log N / \log \log N)$ partitions

$$\begin{array}{ccc} \mathbf{J}_0^{\text{ASY}} \underline{x} & & \mathbf{J}_0^{\text{EVAL}} \underline{x} \\ \hline \mathcal{O}(N(\log N)^2 / \log \log N) & \triangle & \mathcal{O}(N(\log N)^2 / \log \log N) \end{array}$$

Fast evaluation of Schlömilch expansions

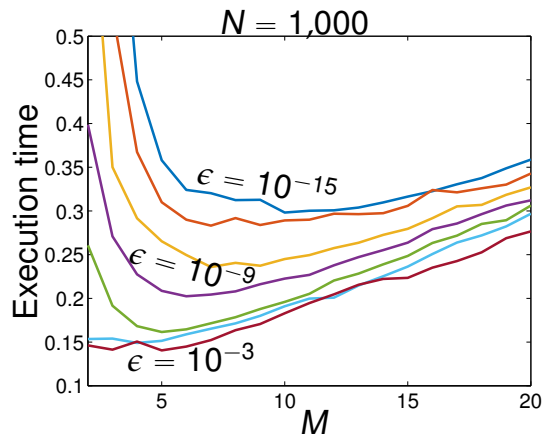
Fix M . But, what M should we pick?

Pick the working tolerance: $\epsilon > 0$:



For computational efficiency:

$$M = \max(\lfloor 0.3 \log(1/\epsilon) \rfloor, 3)$$

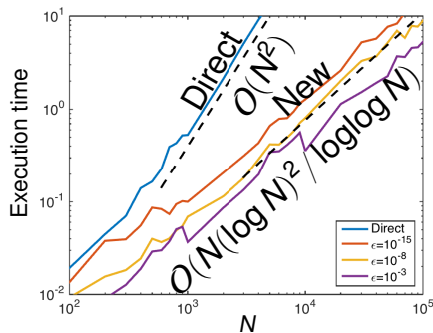


- Other algorithmic parameters are decided upon by precise error bounds.

Fast evaluation of Schlömilch expansions

Analysis-based algorithmic parameters

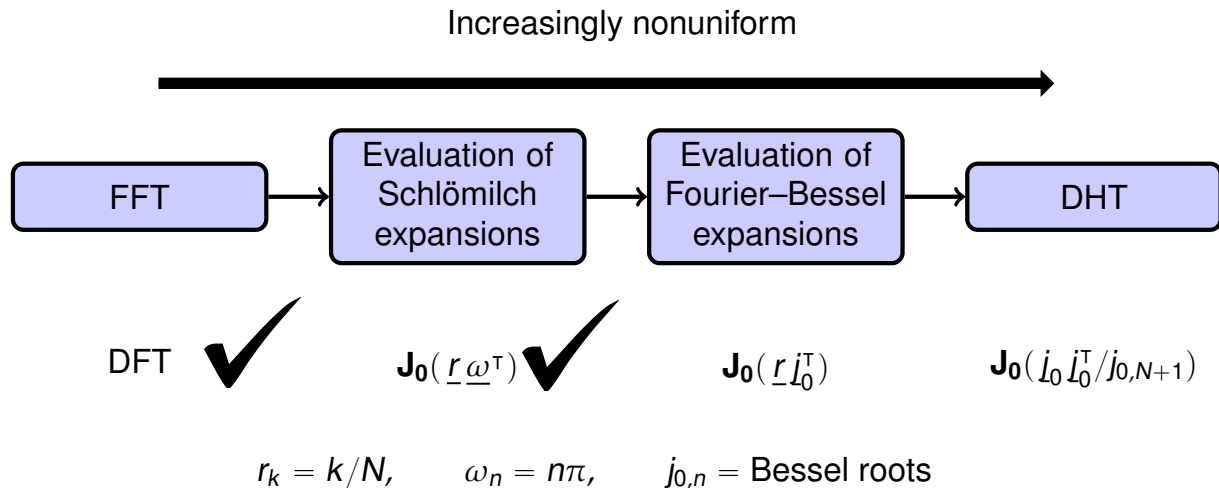
- A handful of FFTs
- Zero offline cost
- Analysis-based \rightarrow guaranteed accuracy



Parameter	Short description	Formula
M	Number of terms in asy	$\max(\lfloor 0.3 \log(1/\epsilon) \rfloor, 3)$
$s_{v,M}(\epsilon)$	$z \geq s_{v,M}(\epsilon) \Rightarrow R_{v,M}(z) \leq \epsilon$	[Table 4.1, T., 15]
α	Partitioning parameter	$(s_{v,M}(\epsilon)/\pi)^{1/2}$
β	Refining parameter	$\min(3/\log N, 1)$
P	Number of partitions	$\lceil \log(30\alpha^{-1}N^{-1/2}) / \log \beta \rceil$

Fast evaluation of Fourier–Bessel expansions

Overview of talk



Goal: FFT-based and analysis-based fast transforms with zero offline cost.

Fast evaluation of Fourier–Bessel expansions

Setup

Fourier–Bessel expansion of $f : [0, 1] \rightarrow \mathbb{C}$ is:

$$f(r) = \sum_{n=1}^N x_n J_0(j_{0,n} r).$$

Aim: A fast algorithm for evaluating $f(r)$ at $r_k = k/N$ for $1 \leq k \leq N$.

Equivalent to the following matrix-vector product:

$$\mathbf{J}_0(\underline{r} \underline{j}_0^T) \underline{x} = \begin{pmatrix} J_0(r_1 j_{0,1}) & \dots & J_0(r_1 j_{0,N}) \\ \vdots & \ddots & \vdots \\ J_0(r_N j_{0,1}) & \dots & J_0(r_N j_{0,N}) \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix}, \quad r_k = k/N, \quad J_0(j_{0,n}) = 0.$$

Fast evaluation of Fourier–Bessel expansions

Bessel roots as a perturbation of an equispaced grid

Idea: Bessel roots are nearly equispaced.

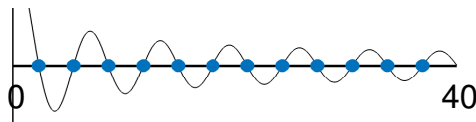
Lemma (Theorem 3 in [Hethcote, 70].)

Let $j_{0,n}$ denote the n th positive root of $J_0(z)$. Then,

$$\left| j_{0,n} - \left(n - \frac{1}{4} \right) \pi \right| \leq \frac{1}{8 \left(n - \frac{1}{4} \right) \pi}.$$

We can write:

$$j_{0,n} = \underbrace{\left(n - \frac{1}{4} \right) \pi}_{\tilde{\omega}_n} + b_n, \quad |b_n| \leq \frac{1}{8 \left(n - \frac{1}{4} \right) \pi}$$



Fast evaluation of Fourier–Bessel expansions

A matrix decomposition

Theorem

For integers $K \geq 1$ and $T \geq 1$ we have

$$\mathbf{J}_0(\underline{r} \underline{l}_0^T) = \mathbf{J}_0(\underline{r} \underline{\tilde{\omega}}^T + \underline{r} \underline{b}^T) = \sum_{s=-K+1}^{K-1} \sum_{t=0}^{T-1} \frac{(-1)^t 2^{-2t+s}}{t!(t-s)!} \overbrace{D_{\underline{r}}^{2t-s} \mathbf{J}_s(\underline{r} \underline{\tilde{\omega}}^T) D_{\underline{b}}^{2t-s}}^{\text{diag-weighted Schlömilch}} + \mathbf{E}_{K,T}.$$

Proof.

Neumann addition formula and Taylor expansion of $J_0(z)$ about $z = 0$. □

$\mathbf{J}_0(\underline{r} \underline{l}_0^T) = \mathbf{A} + \mathbf{E}_{K,T}^{(1)}$

A low-rank correction used for this

Fast evaluation of Fourier–Bessel expansions

Numerical results

Rearrange computation:

For $\epsilon = 10^{-15}$, T and K are:

$$K = 6, \quad T = 3.$$

Looks like

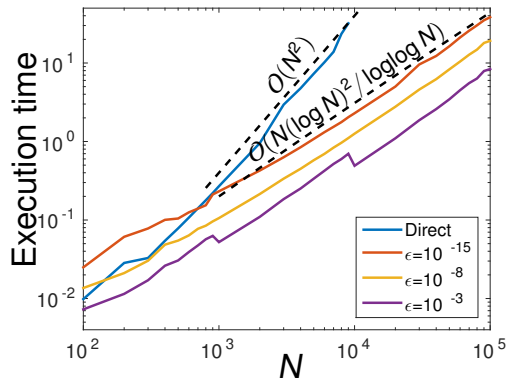
$$\text{Fourier-Bessel} = \underbrace{(2K - 1)T}_{=33} \times \text{Schl\"omilch}$$

But, after rearranging sum:

$$\text{Fourier-Bessel} = \underbrace{(2T + K - 2)}_{=10} \times \text{Schl\"omilch}$$

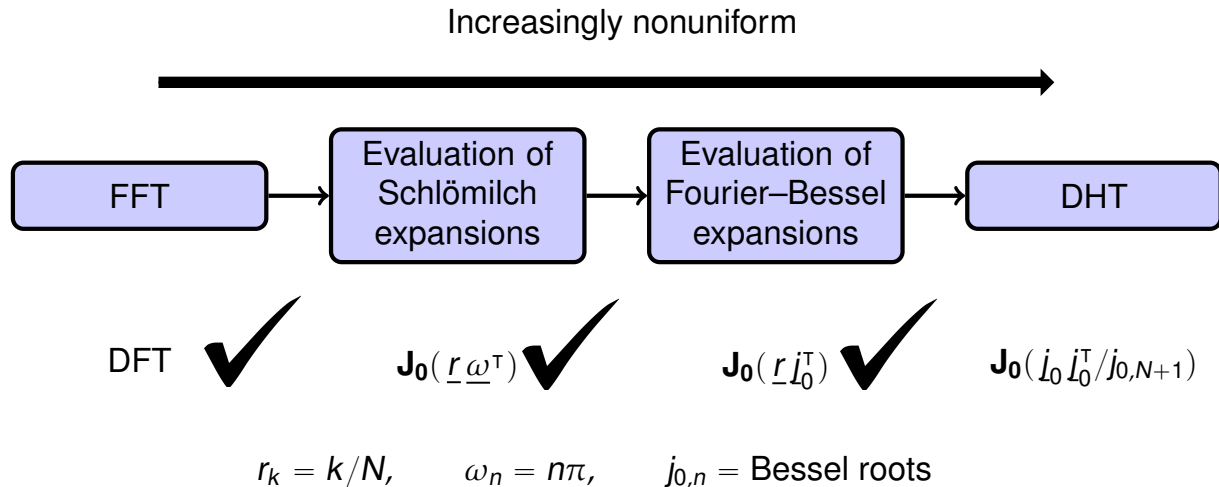
Fourier–Bessel expansions:

$$X_k = \sum_{n=1}^N x_n J_0(j_{0,n}k/N), \quad 1 \leq k \leq N.$$



The discrete Hankel transform

Overview of talk



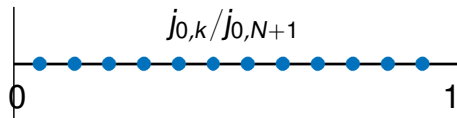
Goal: FFT-based and analysis-based fast transforms with zero offline cost.

The discrete Hankel transform

Discrete Hankel transform

Let $j_{0,k}$ denote the n th positive root of $J_0(z)$. The ratios are nearly equispaced:

$$\left| \frac{j_{0,k}}{j_{0,N+1}} - \frac{k - \frac{1}{4}}{N + \frac{3}{4}} \right| \leq \frac{1}{8(N + \frac{3}{4})(k - \frac{1}{4})\pi^2}.$$



In a similar manner to the Fourier–Bessel case, we have

$$\mathbf{J}_0(\mathbf{j}_0 \mathbf{j}_0^T / j_{0,N+1}) = \mathbf{B} + \mathbf{E}_{K,T}^{(2)}$$

A low-rank correction used for this

The discrete Hankel transform

Numerical results

For $\epsilon = 10^{-15}$, we select:

$$K = 6, \quad T = 3.$$

We have

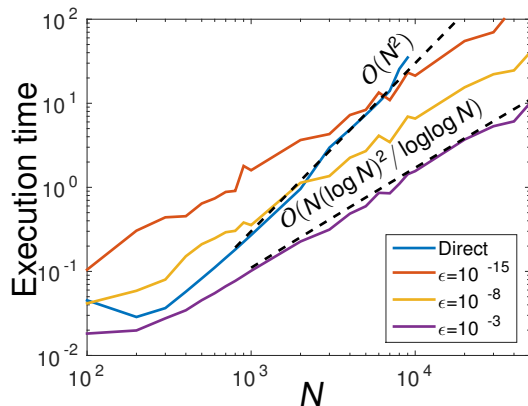
$$\text{DHT} = \underbrace{(2T + K - 2)}_{=10} \times \text{Fourier-Bessel}$$

and

$$\text{DHT} = \underbrace{(2T + K - 2)^2}_{=100} \times \text{Schl\"omilch}$$

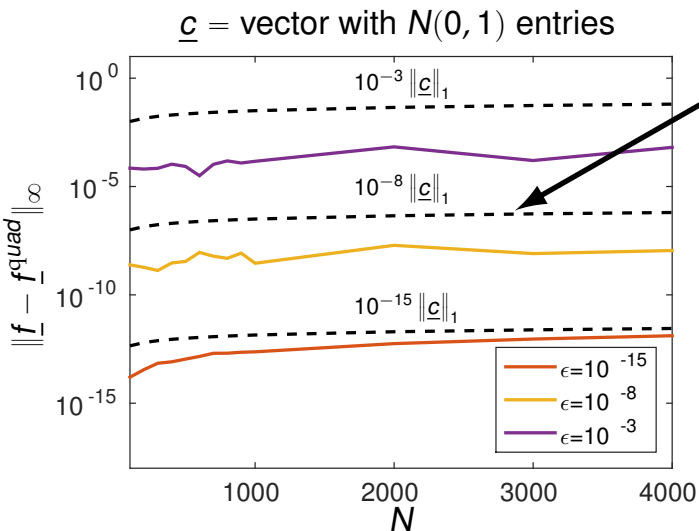
Discrete Hankel transform

$$X_k = \sum_{n=1}^N x_n J_0(j_{0,n} j_{0,k} / j_{0,N+1}), \quad 1 \leq k \leq N.$$



The discrete Hankel transform

Errors in practice versus theory



Theoretical bound

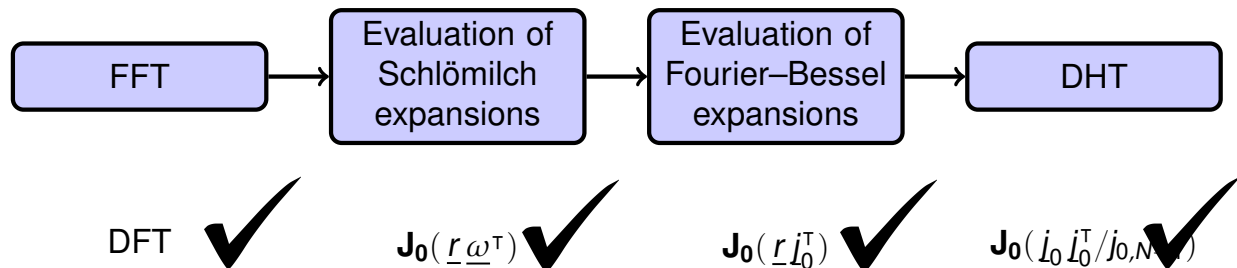
Near-optimal complexity in N
and $\epsilon > 0$:

$$O(N(\log N)^2 \log(1/\epsilon)^p / \log \log N),$$

where

Transform	p
Schlömilch	1
Fourier–Bessel	2
DHT	3

Conclusion



Novel features of our algorithm for the DHT:

1. Zero offline cost.
2. Implementation adapts to individual computer architecture.
3. Guaranteed error control (no heuristics).
4. No hierarchical data structures.

Thank you








Thank you

More information in: T., “A fast analysis-based discrete Hankel transform using asymptotic expansions”, to appear in SINUM.

Code publicly available from:

<https://github.com/ajt60gaibb/FastAsyTransforms>

References

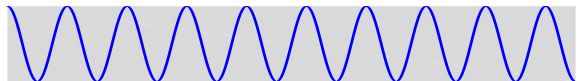
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-  A. Townsend, The race to compute high-order Gauss quadrature, SIAM News, 2015.
-  A. Townsend, A fast analysis-based discrete Hankel transform using asymptotics expansions, to appear in SINUM, 2015.
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Extra slides

Many special functions are trigonometric-like

Trigonometric functions

$\cos(\omega x)$, $\sin(\omega x)$



Chebyshev polynomials

$T_n(x)$

Legendre polynomials

$P_n(x)$

Bessel functions

$J_\nu(z)$

Airy functions

$Ai(x)$

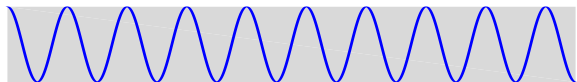
Also, Jacobi polynomials, Hermite polynomials, cylinder functions, etc.

Extra slides

Many special functions are trigonometric-like

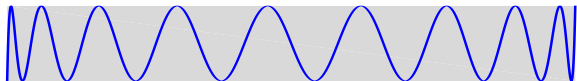
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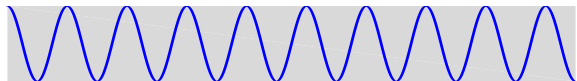
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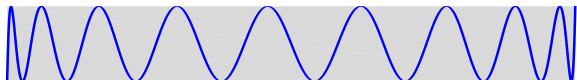
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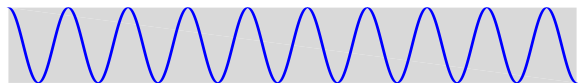
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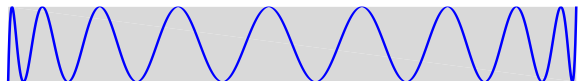
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$T_n(x)$



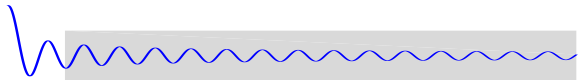
Legendre polynomials

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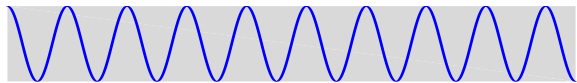
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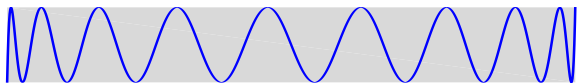
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Chebyshev polynomials

$$T_n(x)$$



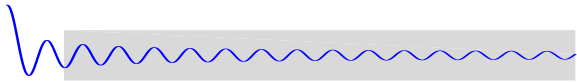
Legendre polynomials

$$P_n(x)$$



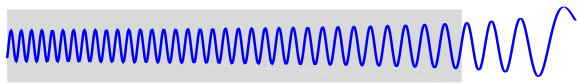
Bessel functions

$$J_\nu(z)$$



Airy functions

$$Ai(x)$$



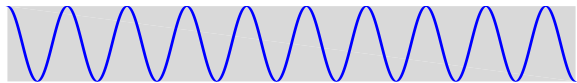
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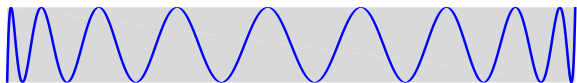
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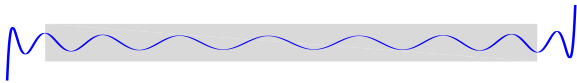
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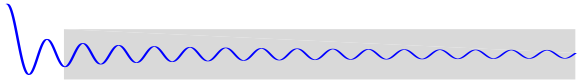
Legendre polynomials

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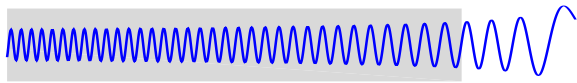
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