

# A static memory sparse spectral method for time-fractional PDEs

**Timon Salar Gutleb**

Oxford Centre for Nonlinear PDE

Mathematical Institute, University of Oxford

**In collaboration with:**

José A. Carrillo

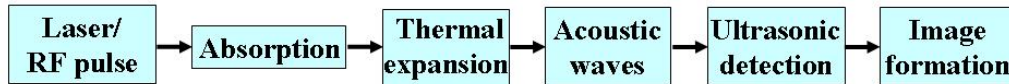
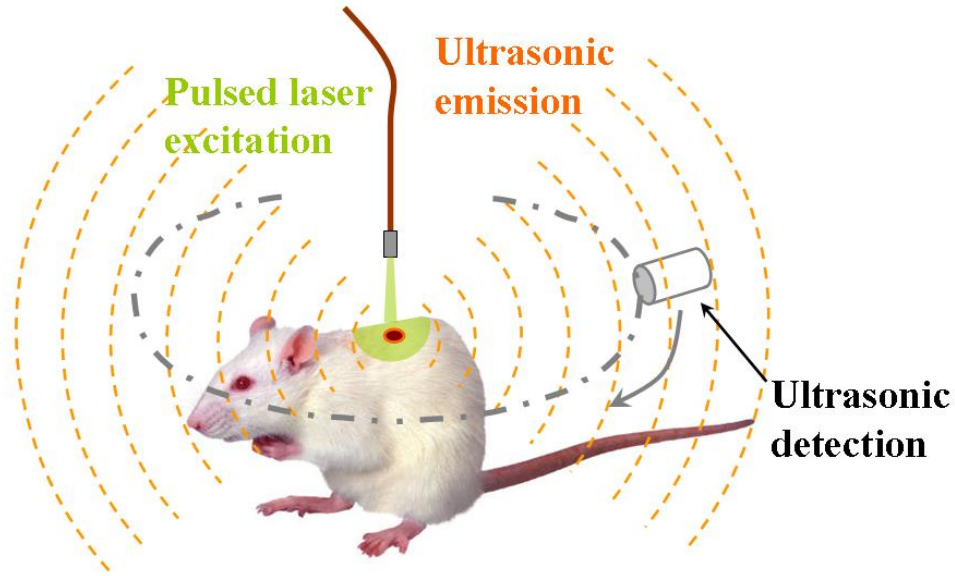
## Talk structure

1. Motivation from photoacoustic ultrasound imaging
  2. The Yuan-Agrawal method for Caputo derivatives
  3. A static memory, sparse and recursive solver
  4. Numerical experiments
-

# 1. Motivation from photoacoustic ultrasound imaging

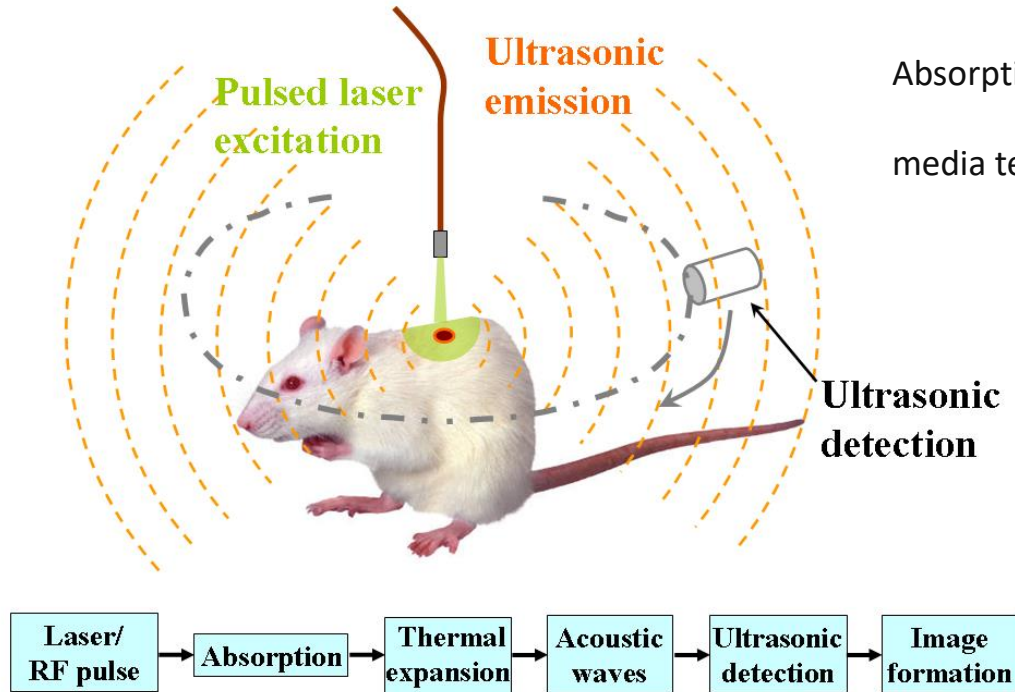
---

## 1. Motivation from photoacoustic ultrasound imaging



## 1. Motivation from photoacoustic ultrasound imaging

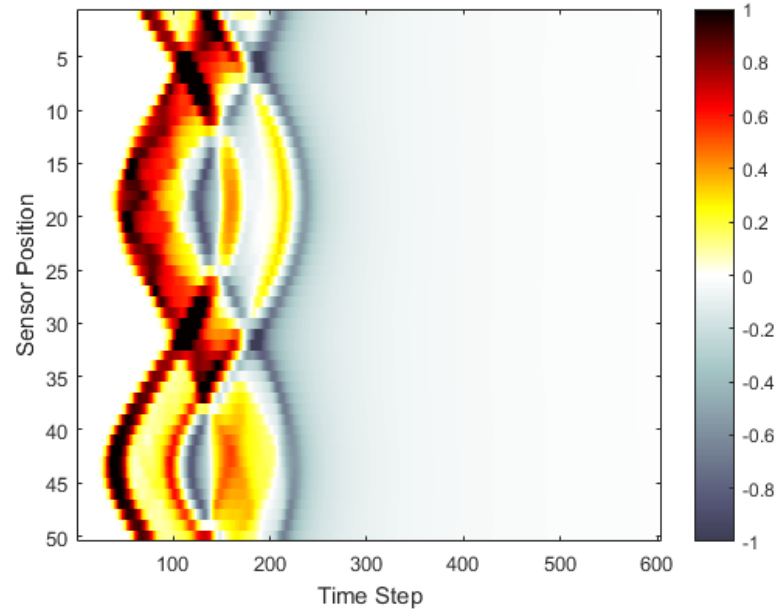
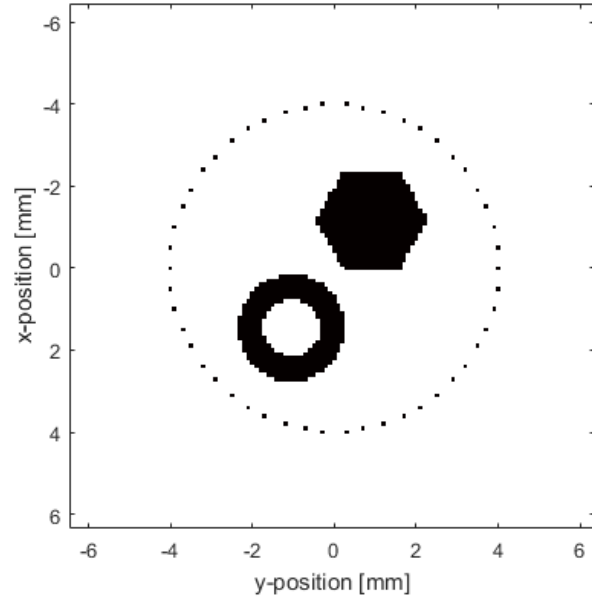
Absorption of compressional and shear waves in viscoelastic media tend to follow a frequency power law<sup>[1]</sup>.



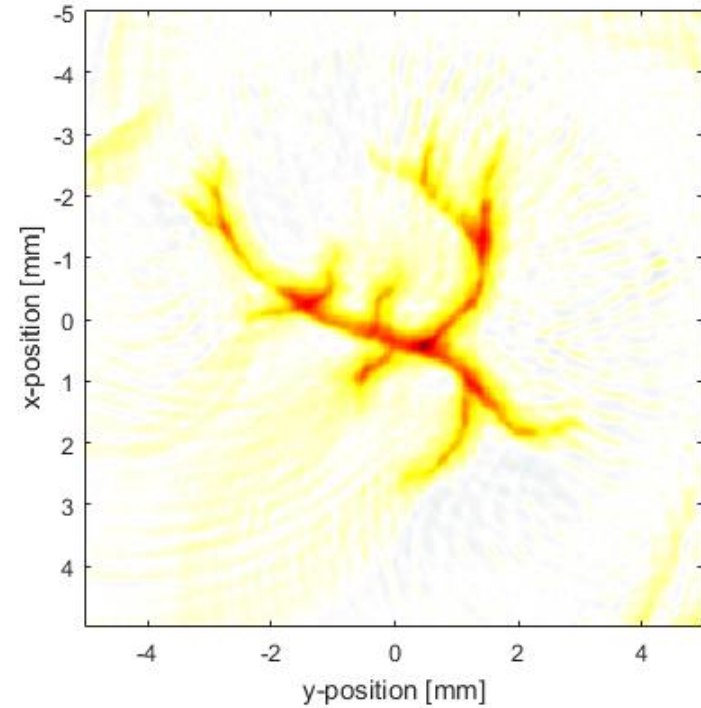
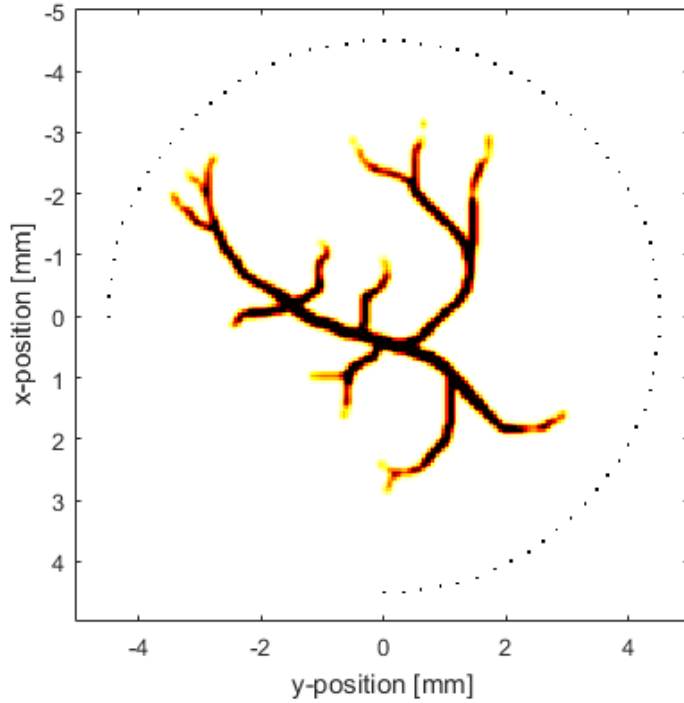
$$\mathbf{u} = \nabla\phi + \nabla \times \Psi$$

$$0 = \nabla \left( \frac{\partial^2 \phi}{\partial t^2} - c_p^2 \nabla^2 \phi - \tau_p c_p^2 \frac{\partial^{y-1}}{\partial t^{y-1}} \nabla^2 \phi \right) + \nabla \times \left( \frac{\partial^2 \Psi}{\partial t^2} - c_s^2 \nabla^2 \Psi - \tau_s c_s^2 \frac{\partial^{y-1}}{\partial t^{y-1}} \nabla^2 \Psi \right).$$

## 1. Motivation from photoacoustic ultrasound imaging



## 1. Motivation from photoacoustic ultrasound imaging



## 2. The Yuan-Agrawal method for Caputo derivatives

---



Definition (Caputo derivative):

$$\frac{\partial^\alpha}{\partial t^\alpha} f(t) = D_C^\alpha f(t) = \frac{1}{\Gamma([\alpha] - \alpha)} \int_0^t (t - s)^{([\alpha] - \alpha - 1)} f^{([\alpha])}(s) ds,$$

Inherent challenge: Non-local in time  $\rightarrow$  Memory accumulation

Treeby & Cox's solution:

Transform the *time*-fractional into a *space*-fractional problem.

$$\frac{1}{c_0^2} \frac{\partial^2}{\partial t^2} \phi - \nabla^2 \phi - \tau \frac{\partial^{y-1}}{\partial t^{y-1}} \nabla^2 \phi = 0.$$



$$\frac{1}{c_0^2} \frac{\partial^2 \phi}{\partial t^2} - \nabla^2 \phi - \tau_1 (-\nabla^2)^{y/2} \frac{\partial \phi}{\partial t} - \tau_2 (-\nabla^2)^{(y+1)/2} \phi = 0.$$

## 2. The Yuan-Agrawal method for Caputo derivatives

Treeby & Cox's solution:

Transform the *time*-fractional into a *space*-fractional problem.

$$\frac{1}{c_0^2} \frac{\partial^2}{\partial t^2} \phi - \nabla^2 \phi - \tau \frac{\partial^{y-1}}{\partial t^{y-1}} \nabla^2 \phi = 0.$$



$$\mathcal{F}_{x,t} \left\{ \frac{\partial^y g(x,t)}{\partial t^y} \right\} = (-i\omega)^y G(k, \omega).$$

$\omega\tau \ll 1$

$$\frac{1}{c_0^2} \frac{\partial^2 \phi}{\partial t^2} - \nabla^2 \phi - \tau_1 (-\nabla^2)^{y/2} \frac{\partial \phi}{\partial t} - \tau_2 (-\nabla^2)^{(y+1)/2} \phi = 0.$$

## 2. The Yuan-Agrawal method for Caputo derivatives

**THEOREM 3.1** (Generalized Yuan–Agrawal–Caputo derivative). *Let  $\alpha > 0$ ,  $\alpha \notin \mathbb{N}$  and  $f \in C^{[\alpha]}[0, T]$ . Then the Caputo fractional derivative of  $f$  can be expressed as*

$$\frac{\partial^\alpha}{\partial t^\alpha} f(t) = \int_0^\infty \phi(w, t) dw,$$

where the function  $\phi_f : (0, \infty) \times [0, T] \rightarrow \mathbb{R}$  is defined by

$$\phi_f(w, t) := \frac{(-1)^{[\alpha]} 2 \sin(\pi\alpha)}{\pi} w^{2\alpha-2[\alpha]+1} \int_0^t e^{-w^2(t-\tau)} \frac{\partial^{[\alpha]}}{\partial \tau^{[\alpha]}} f(\tau) d\tau.$$

Furthermore, for fixed  $w > 0$  the function  $\phi_f(w, t)$  satisfies the (non-fractional) differential equation

$$(3.1) \quad \frac{\partial}{\partial t} \phi_f(w, t) = -w^2 \phi_f(w, t) + \frac{(-1)^{[\alpha]} 2 \sin(\pi\alpha)}{\pi} w^{2\alpha-2[\alpha]+1} \frac{\partial^{[\alpha]}}{\partial t^{[\alpha]}} f(t),$$

with initial condition  $\phi(w, 0) = 0$ .

Criticism of the Yuan-Agrawal method:

Gauss-Laguerre quadrature tends to work very poorly for these problems and requires prohibitively large number of nodes.

A solution to this was proposed by Diethelm<sup>[1]</sup> (and Birk & Song<sup>[2]</sup>):

$$\int_0^{\infty} \phi_f(w, t) dw = \int_{-1}^1 (1 - \kappa)^{\bar{\alpha}} (1 + \kappa)^{-\bar{\alpha}} \bar{\phi}_f(\kappa, t) d\kappa,$$

$$\bar{\phi}_f(\kappa, t) := 2(1 - \kappa)^{-\bar{\alpha}} (1 + \kappa)^{\bar{\alpha}-2} \phi_f\left(\frac{1 - \kappa}{1 + \kappa}, t\right).$$

### 3. A static memory, sparse and recursive solver

---

Restate Yuan-Agrawal method in recursive form:

$$\frac{\partial^\alpha}{\partial t^\alpha} f(t) \approx \sum_{j=1}^L A_j \int_0^t e^{-s_j^2(t-\tau)} \frac{\partial^{[\alpha]}}{\partial \tau^{[\alpha]}} f(\tau) d\tau = \sum_{j=1}^L A_j \psi_j(t),$$

$$\psi_j(t) := \int_0^t e^{-s_j^2(t-\tau)} \frac{\partial^{[\alpha]}}{\partial \tau^{[\alpha]}} f(\tau) d\tau.$$



$$\psi_j(t) = e^{-s_j^2 \Delta t} \psi_j(t - \Delta t) + \int_{t-\Delta t}^t e^{-s_j^2(t-\tau)} \frac{\partial^{[\alpha]}}{\partial \tau^{[\alpha]}} f(\tau) d\tau.$$

Resolve spatial dependence in multivariate orthogonal polynomials:

$$f(n\Delta t, \mathbf{x}) = \mathbf{P}(\mathbf{x}) \mathbf{f}(n\Delta t),$$

$$\psi_j(n\Delta t, \mathbf{x}) = \mathbf{P}(\mathbf{x}) \psi_j(n\Delta t).$$

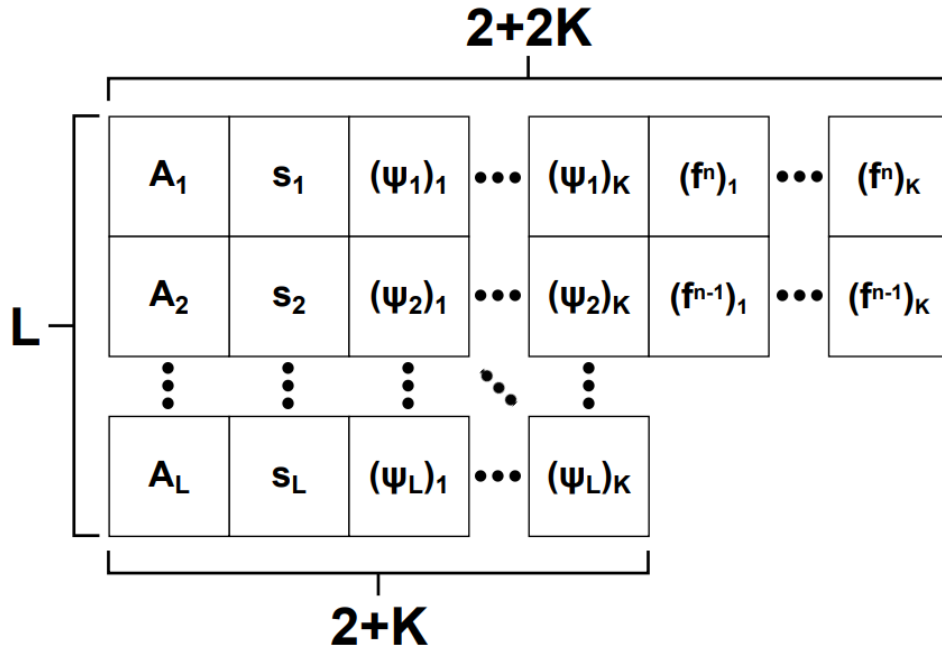
We obtain:

$$\left( \frac{\partial^\alpha f}{\partial t^\alpha} \right) (n\Delta t, \mathbf{x}) \approx \mathbf{P}(\mathbf{x}) \sum_{j=1}^L A_j \left( e^{-s_j^2 \Delta t} \boldsymbol{\psi}_j^{n-1} + \frac{(1 - e^{-s_j^2 \Delta t})}{s_j^2 \Delta t} (\mathbf{f}^n - \mathbf{f}^{n-1}) \right),$$

$$\psi(n\Delta t, \mathbf{x}) = \mathbf{P}(\mathbf{x}) \psi(n\Delta t) \approx \mathbf{P}(\mathbf{x}) \boldsymbol{\psi}_j^n = \mathbf{P}(\mathbf{x}) \left( e^{-s_j^2 \Delta t} \boldsymbol{\psi}_j^{n-1} + \frac{(1 - e^{-s_j^2 \Delta t})}{s_j^2} \frac{\mathbf{f}^n - \mathbf{f}^{n-1}}{\Delta t} \right).$$



The memory requirements of computing a Caputo derivative:



$L(2+K)+2K$ , where

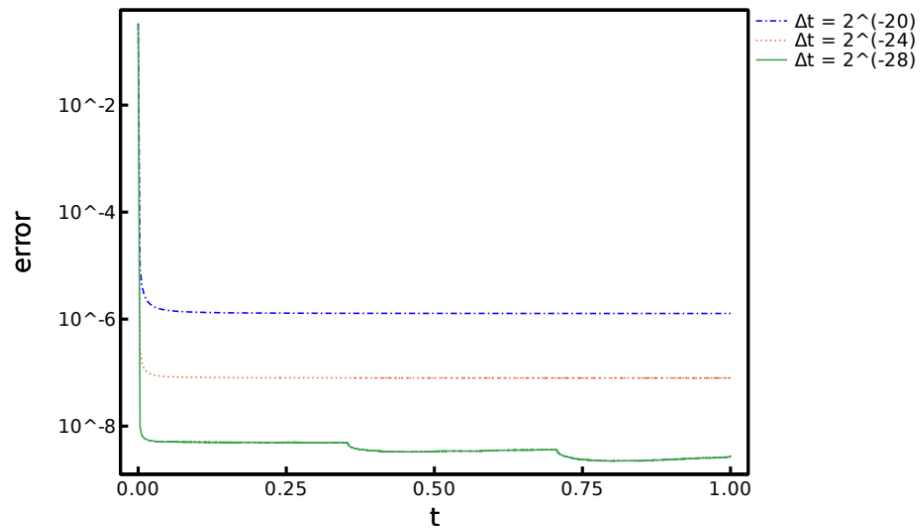
$L$  ... number of quadrature pts.

$K$  ... degree of polynomial approx.

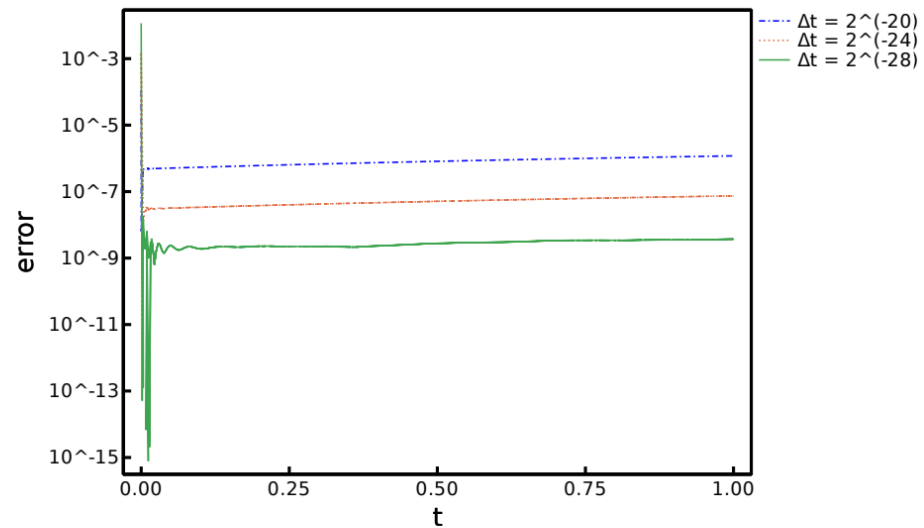
## 4. Numerical experiments

---

#### 4. Numerical experiments



(a)  $f(t) = t^2$ ,  $L = 65$ ,  $\alpha = \frac{2}{3}$

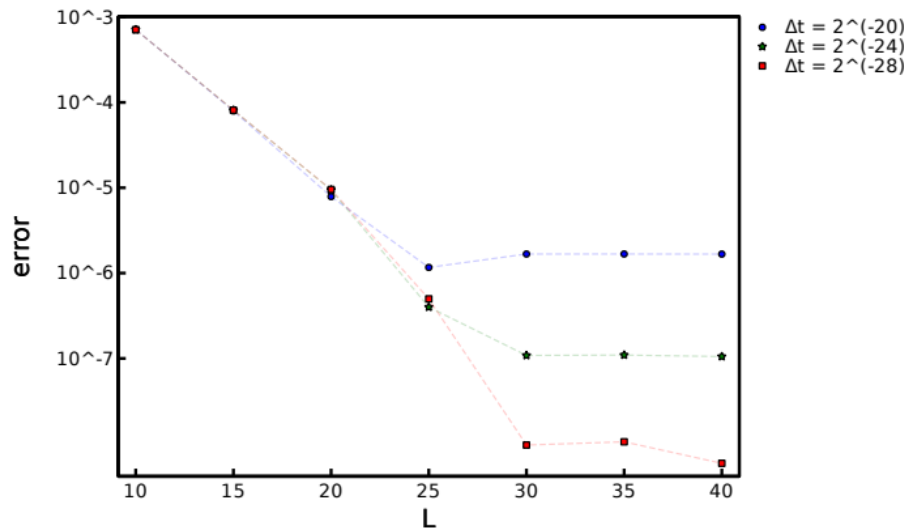


(b)  $f(t) = e^t$ ,  $L = 60$ ,  $\alpha = \frac{1}{2}$

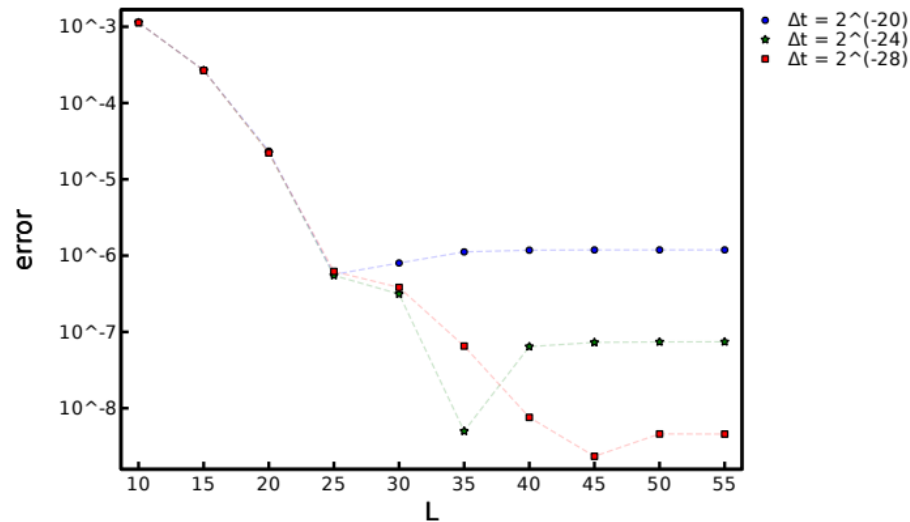
#### 4. Numerical experiments

$$\left| \left( \frac{\partial^\alpha}{\partial t^\alpha} f \right) (T, \mathbf{x}) - \mathbf{P}(\mathbf{x}) \mathcal{P}_K \sum_{j=1}^L A_j \psi_j^N \right|$$

$$\leq \frac{M(\mathbf{x})}{(2L)!} + C(\mathbf{x}) L T \Delta t + \text{err}_{\mathbf{P}, K} \left( \sum_{j=1}^L A_j \psi_j(T, \mathbf{x}) \right).$$

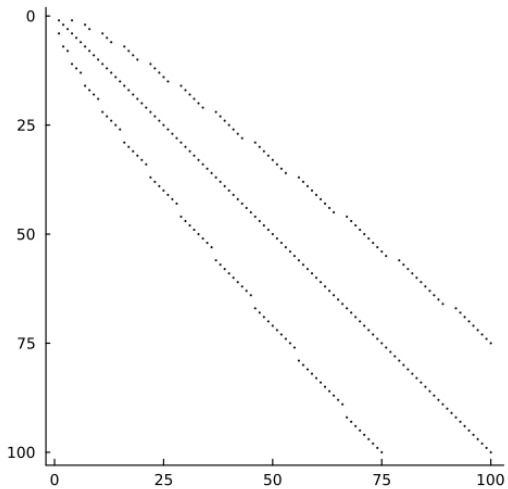


(a)  $f(t) = t^2$ ,  $\alpha = \frac{1}{4}$



(b)  $f(t) = e^t$ ,  $\alpha = \frac{1}{2}$

Discretize our equation of interest on the unit disk:

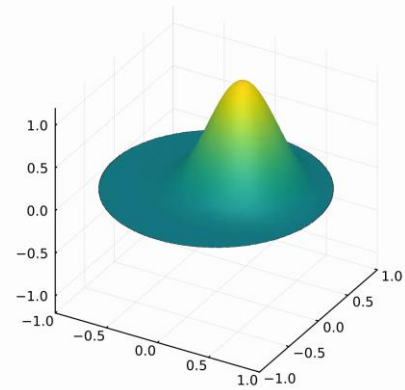
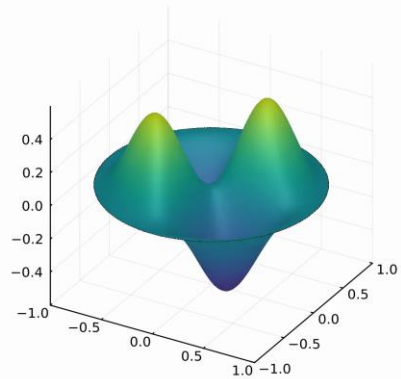
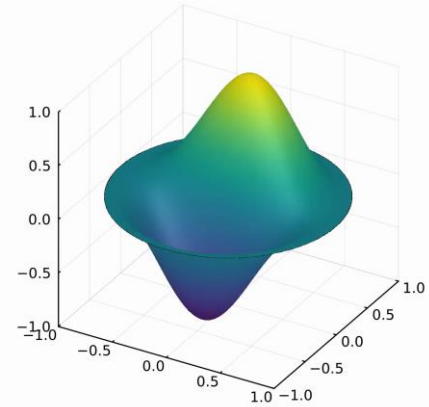
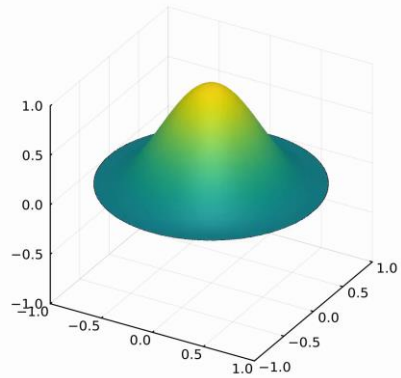


$$\frac{1}{c_0^2} \frac{\partial^2}{\partial t^2} f - \Delta f + \tau \frac{\partial^\alpha}{\partial t^\alpha} f = 0,$$

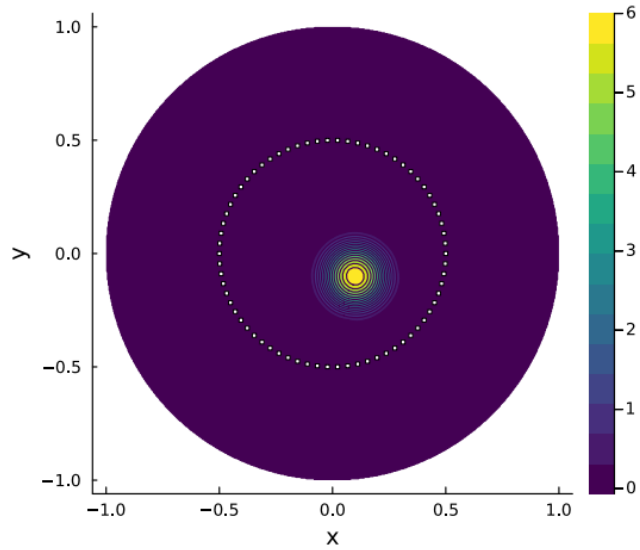


$$\mathbf{Z}^{(1)}(r, \theta) \left( \left( \frac{1}{c_0^2 \Delta t} + \tau \left( \sum_{j=1}^L A_j \frac{1 - e^{-s_j^2 \Delta t}}{s_j^2} \right) \right) \mathcal{C} - (\Delta t) \Delta \right) \mathbf{f}^n =$$

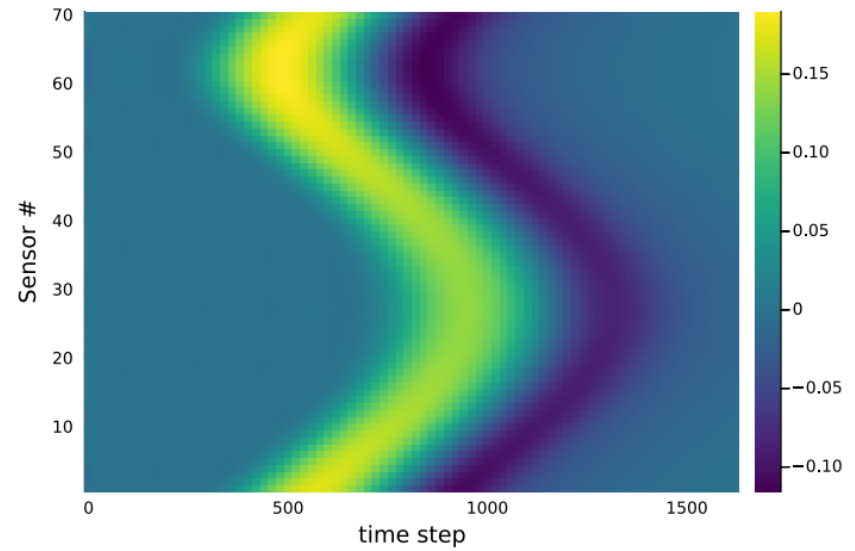
$$\mathbf{Z}^{(1)}(r, \theta) \mathcal{C} \left( \left( \frac{2}{c_0^2 \Delta t} + \tau \sum_{j=1}^L A_j \frac{1 - e^{-s_j^2 \Delta t}}{s_j^2} \right) \mathbf{f}^{n-1} - \frac{\mathbf{f}^{n-2}}{c_0^2 \Delta t} - \tau \sum_{j=1}^L A_j e^{-s_j^2 \Delta t} \boldsymbol{\psi}_j^{n-1} \right),$$



## Modeling circular sensor arrays:



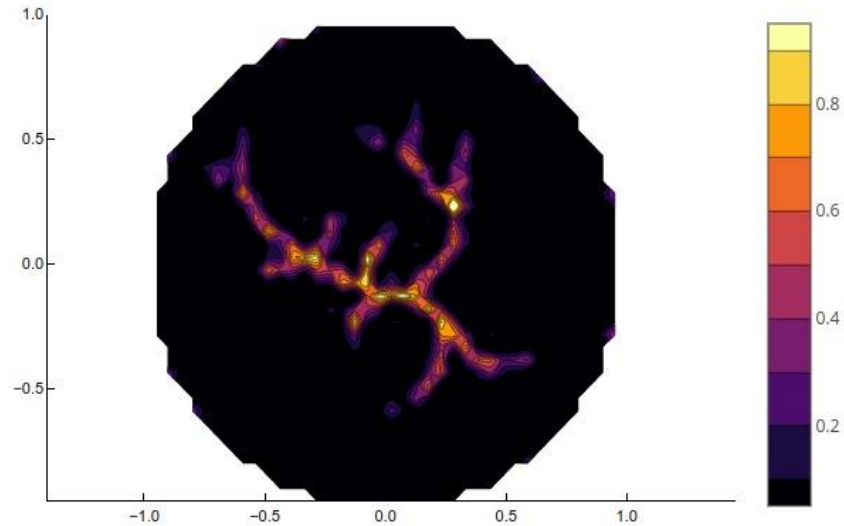
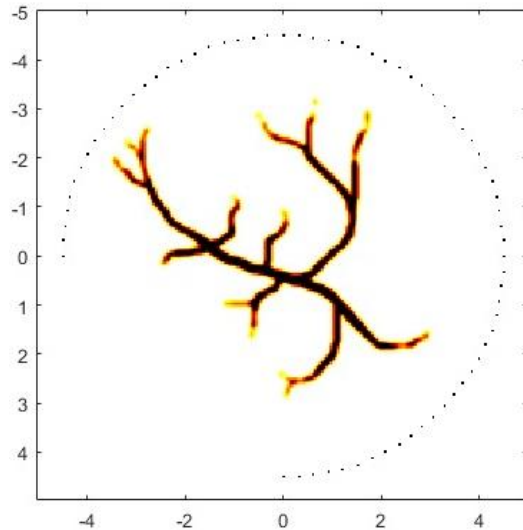
(a)



(b)

Next goals:

- Fully realized image reconstruction
- Comparison with fractional Laplacian methods
- Combine with spectral element methods on annular domains





# A static memory sparse spectral method for time-fractional PDEs

**Timon Salar Gutleb**

Oxford Centre for Nonlinear PDE

Mathematical Institute, University of Oxford

**In collaboration with:**

José A. Carrillo