Fast numerical methods and mathematical analysis for space-fractional PDEs

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- Diffusion processes
 - describe the spreading of particles due to their random movements
 - are ubiquitous in nature, natural and social sciences, and engineering
- Since it was proposed in 1855, the classical diffusion equation
 - has been widely used in different disciplines
 - has generated satisfactory results in various applications
- However, certain diffusion processes cannot be described by the Fickian diffusion equation. They exhibit anomalous diffusion behavior
 - Photocopiers and laser printers played an important role in the study
 - In groundwater contaminant transport, remediation
 - is often not as effective as predicted by the classical diffusion equation
 - may take decades or centuries longer than previously thought
 - Increasingly more diffusion processes have been found to be non-Fickian (Metzler & Klafter, Phys. Rep., 339:1-77, 2000)
 - signaling of biological cells, anomalous electrodiffusion in nerve cells
 - foraging behavior of animals, electrochemistry, physics, finance
 - fluid and continuum mechanics, viscoelastic and viscoplastic flow

$$\frac{\partial u}{\partial t} - d_+(x,t)\frac{\partial^{\alpha} u}{\partial_+ x^{\alpha}} - d_-(x,t)\frac{\partial^{\alpha} u}{\partial_- x^{\alpha}} = f, \quad x \in (x_l, x_r), \ t \in (0,T], \quad (1)$$
$$u(x_l,t) = u(x_r,t) = 0, \ t \in [0,T], \quad u(x,0) = u_0(x), \ x \in [x_l, x_r].$$

- $\bullet \ 1 < \alpha < 2$ is the order of the anomalous diffusion
- d_+ and d_- are the left- and right-sided diffusivity coefficients
- The left- and right-sided fractional derivatives are defined by

$$\frac{\partial^{\alpha} u(x,t)}{\partial_{+}x^{\alpha}} := \lim_{h \to 0^{+}} \frac{1}{h^{\alpha}} \sum_{\substack{k=0 \ (x_{r}-x)/h \rfloor}}^{\lfloor (x-x_{l})/h \rfloor} g_{k}^{(\alpha)} u(x-kh,t), \qquad (2)$$

$$\frac{\partial^{\alpha} u(x,t)}{\partial_{-}x^{\alpha}} := \lim_{h \to 0^{+}} \frac{1}{h^{\alpha}} \sum_{\substack{k=0 \ k=0}}^{\lfloor (x_{r}-x)/h \rfloor} g_{k}^{(\alpha)} u(x+kh,t)$$

• $g_k^{(\alpha)} := (-1)^k {\alpha \choose k}$ with ${\alpha \choose k}$ being the fractional binomial coefficients.

Fractional finite difference method

- The fully implicit finite difference method with a direct truncation of the series in (2) is unconditionally unstable (Meerschaert & Tadjeran, J. Comput. Appl. Math., 2004)!
- They utilized a shifted Grünwald approximation to derive an unconditionally stable finite difference method

$$\frac{u_i^m - u_i^{m-1}}{\Delta t} - \frac{d_i^{+,m}}{h^{\alpha}} \sum_{k=0}^{i+1} g_k^{(\alpha)} u_{i-k+1}^m - \frac{d_i^{-,m}}{h^{\alpha}} \sum_{k=0}^{N-i+1} g_k^{(\alpha)} u_{i+k-1}^m = f_i^m \quad (3)$$

The finite difference method can be written in the matrix form

$$(I + \Delta t A^m) u^m = u^{m-1} + \Delta t f^m.$$
⁽⁴⁾

- A^m is a full (or dense) diagonally dominant M-matrix.
- The scheme is only of first-order accuracy in space and time!

Computational and memory cost of fractional numerical methods

- The stiffness matrix A^m is a dense or full matrix, traditionally
 - ${\, \bullet \,}$ The scheme was inverted in ${\cal O}(N^3)$ of operations per time step
 - The scheme was stored in ${\cal O}(N^2)$ of memory
- Each time the mesh size and time step are refined by half
 - The total number of unknowns increases 2 times for 1D problems
 - The computational work increases $2^3 \times 2 = 16$ times
 - The memory increases by 4 times.
 - The total number of unknowns increases 4 times for 2D problems
 - The computational work increases $4^3 \times 2 = 128$ times
 - The memory increases by 16 times.
 - The total number of unknowns increases 8 times for 3D problems
 - The computational work increases $8^3 \times 2 = 1024$ times
 - The memory increases by 64 times.
- The significantly increased computational and memory cost of the numerical methods calls for the development of fast and faithful numerical methods with efficient memory storage.

A fast two-step operator-splitting finite difference method (W., K. Wang, & Sircar, J. Comput. Phys., 2010)

• The development of a fast methods replies on the stiffness matrix ${\cal A}^m = [a^m_{i,j}/h^{lpha}]^N_{i,j=1}$

$$a_{i,j}^{m} = \begin{cases} -(d_{i}^{+,m} + d_{i}^{-,m})g_{1}^{(\alpha)} > 0, & j = i, \\ -(d_{i}^{+,m}g_{2}^{(\alpha)} + d_{-,i}^{m+1}g_{0}^{(\alpha)}) < 0, & j = i-1, \\ -(d_{i}^{+,m}g_{0}^{(\alpha)} + d_{i}^{-,m}g_{2}^{(\alpha)}) < 0, & j = i+1, \\ -d_{i}^{+,m}g_{i-j+1}^{(\alpha)} < 0, & j < i-1, \\ -d_{i}^{-,m}g_{j-i+1}^{(\alpha)} < 0, & j > i+1. \end{cases}$$
(5)

- A^m is a full matrix
- **2** A^m has a special structure
- **③** The information A^m is sparse ($\approx 3N$).

• We utilize the following properties of $g_k^{(\alpha)} := (-1)^k {\alpha \choose k}$ to conclude

$$g_{1}^{(\alpha)} = -\alpha < 0, \quad 1 = g_{0}^{(\alpha)} > g_{2}^{(\alpha)} > g_{3}^{(\alpha)} > \dots > 0,$$

$$\sum_{k=0}^{\infty} g_{k}^{(\alpha)} = 0, \quad \sum_{k=0}^{m} g_{k}^{(\alpha)} < 0 \quad (m \ge 1),$$

$$g_{k}^{(\alpha)} = \frac{\Gamma(k-\alpha)}{\Gamma(-\alpha)\Gamma(k+1)} = \frac{1}{\Gamma(-\alpha)k^{\alpha+1}} \left(1 + O\left(\frac{1}{k}\right)\right)$$
(6)

• $a_{i,i\pm k}/a_{i,i}$ decay at a rate of $1/k^{\alpha+1}$ as $k \to \infty$.

$$a_{i,i}^{m} - \sum_{j=1,j\neq i}^{N} |a_{i,j}^{m}| = -(d_{+,i}^{m} + d_{-,i}^{m})g_{1}^{(\alpha)} - d_{i,+}^{m} \sum_{k=0,k\neq 1}^{i} g_{k}^{(\alpha)} - d_{-,i}^{m} \sum_{k=0,k\neq 1}^{N-i} g_{k}^{(\alpha)}$$
(7)
> $-(r_{+,i}^{m+1} + r_{-,i}^{m+1})g_{1}^{(\alpha)} - (r_{i,+}^{m+1} + r_{-,i}^{m+1}) \sum_{k=0,k\neq 1}^{\infty} g_{k}^{(\alpha)} = 0.$

• *A^m* is a strictly diagonally dominant M-matrix, so the scheme is monotone.

Based on the properties of the stiffness matrix A^m of the difference method

$$(I + \Delta t A^m) u^m = u^{m-1} + \Delta t f^m,$$

• Split the stiffness matrix A^m as $A^m = A^m_k + A^m_o$ with the properties

- A_k^m contains the 2k + 1 diagonals of A^m and is zero elsewhere
- ${\it A}_k^m$ approximates ${\it A}^m$ asymptotically as $N
 ightarrow \infty$
- $A_o^m v$ can be computed efficiently for any vector v

• Derivation of a fast operator-splitting finite difference method

- Substitute the decomposition $A^m = A_k^m + A_o^m$ into (4).
- Move $A_o^m u^m$ to the right-hand side and approximate the u^m by a linear extrapolation of u^{m-2} and u^{m-1} .

$$(I + \Delta t A_k^m) u^m = (I - 2\Delta t A_o^m) u^{m-1} + \Delta t A_o^m u^{m-2} + \Delta t f^m, \ m \ge 1,$$

$$(I + \Delta t A_k^1) u^1 = (I - \Delta t A_o^1) u^0 + \Delta t f^1.$$
(8)

Scheme (5) with $k = \log N$ has the approximation property

$$\frac{\left\|\boldsymbol{A}_{o}^{m}\right\|_{\infty}}{\left\|\boldsymbol{A}^{m}\right\|_{\infty}} = \frac{\left\|\boldsymbol{A}^{m} - \boldsymbol{A}_{k}^{m}\right\|_{\infty}}{\left\|\boldsymbol{A}^{m}\right\|_{\infty}} = O(\log^{-\alpha} N) \to 0 \qquad as \ N \to \infty.$$
(9)

$$\begin{split} \left\| \mathcal{A}_{o}^{m} \right\|_{\infty} &= h^{-\alpha} \max_{i=1,\dots,N} \left(d_{i}^{-,m} + d_{i}^{+,m} \right) \sum_{l>k=\log N} g_{l+1}^{(\alpha)} \\ &= h^{-\alpha} \max_{i=1,\dots,N} \left(d_{i}^{-,m} + d_{i}^{+,m} \right) \sum_{l>k} \frac{1}{\Gamma(-\alpha)k^{\alpha+1}} \left(1 + O\left(\frac{1}{k}\right) \right) \\ &= h^{-\alpha} \max_{i=1,\dots,N} \left(d_{i}^{-,m} + d_{i}^{+,m} \right) O\left(\frac{1}{k^{\alpha}}\right), \end{split}$$
(10)

$$\|A^m\|_{\infty} > \alpha h^{-\alpha} \max_{i=1,\dots,N} (d_i^{-,m} + d_i^{+,m}).$$

The ratio of the two preceding estimates gives the desired result.

The stiffness matrix A^m can be stored in 3N + 2 of memory.

 A^m can be decomposed as

$$\mathbf{A}^{m} = h^{-\alpha} \left(\operatorname{diag}(d_{i}^{+,m})_{i=1}^{N} \mathbf{A}_{L}^{\alpha,N} + \operatorname{diag}(d_{i}^{-,m})_{i=1}^{N} \mathbf{A}_{R}^{\alpha,N} \right)$$
(11)

with $A_L^{\alpha,N}$ being defined below and $A_R^{\alpha,N} = (A_L^{\alpha,N})^T$

$$A_{L}^{\alpha,N} := - \begin{bmatrix} g_{1}^{(\alpha)} & g_{0}^{(\alpha)} & 0 & \dots & 0 & 0 \\ g_{2}^{(\alpha)} & g_{1}^{(\alpha)} & g_{0}^{(\alpha)} & \ddots & \ddots & 0 \\ \vdots & g_{2}^{(\alpha)} & g_{1}^{(\alpha)} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & 0 \\ g_{N-1}^{(\alpha)} & \ddots & \ddots & \ddots & g_{1}^{(\alpha)} & g_{0}^{(\alpha)} \\ g_{N-1}^{(\alpha)} & g_{N-1}^{(\alpha)} & \dots & g_{2}^{(\alpha)} & g_{1}^{(\alpha)} \end{bmatrix} .$$

$$\bullet \ h, \ (d_{i}^{+,m})_{i=1}^{N}, \ (d_{i}^{-,m})_{i=1}^{N}, \ \text{and} \ A_{L}^{\alpha,N} \ \text{contain} \ 3N + 2 \ \text{parameters.}$$
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10 / 34

$A^m v$ can be evaluated in $O(N \log N)$ operations for any vector v.

The matrix ${\cal A}_L^{lpha,N}$ is embedded into a 2N imes 2N circulant matrix $C_{2N,L}$

$$C_{2N,L} := \begin{bmatrix} A_L^{\alpha,N} & C_L^{\alpha,N} \\ C_L^{\alpha,N} & A_L^{\alpha,N} \end{bmatrix}, \qquad u_{2N} = \begin{bmatrix} \mathbf{v} \\ 0 \end{bmatrix},$$

$$C_L^{\alpha,N} := -\begin{bmatrix} 0 & g_N^{(\alpha)} & \dots & \dots & g_3^{(\alpha)} & g_2^{(\alpha)} \\ 0 & 0 & g_N^{(\alpha)} & \dots & \ddots & g_3^{(\alpha)} \\ 0 & 0 & 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & \ddots & 0 & g_N^{(\alpha)} \\ g_0^{(\alpha)} & 0 & \dots & 0 & 0 & 0 \end{bmatrix}.$$
(12)

- We can similarly define another $2N \times 2N$ circulant matrix $C_{2N,R}$
- A circulant matrix C_{2N} can be decomposed as

$$C_{2N} = F_{2N}^{-1} \operatorname{diag}(F_{2N} \boldsymbol{c}_{2N}) F_{2N}$$
(13)

where F_{2N} is the $2N \times 2N$ discrete Fourier transform matrix and c_{2N} is the first column vector of C_{2N} .

- $F_{2N}u_{2N}$ can be carried out in $O(N \log N)$ operations via FFT.
- $C_{2N}u_{2N}$ can be evaluated in $O(N \log N)$ operations.
- $A_L^{\alpha,N} u$ and $A_R^{\alpha,N} u$ can be evaluated in $O(N \log N)$ operations.
- $A^m u$ can be evaluated in $O(N \log N)$ operations.
- The right-hand side of the finite difference method (5) can be evaluated in $O(N \log N)$ operations!

Theorem

The fast finite difference method (5) can be inverted in $O(N \log^2 N)$ of operations per time step using $O(N \log N)$ of memory.

- Remarks on the fast finite difference method
 - It is not lossy, since no compression is involved.
 - Stability and convergence of the method yet to be proved
 - A fast conjugate gradient iterative solver can be used to solve the original (single-step) finite difference method, which has proved stability and convergence.
- Development of other fast methods
 - A fast Crank-Nicolson scheme of similar computational and storage cost (Basu & W., Int'l J. Numer. Anal. Modeling, 2012). Crank-Nicolson scheme with a Richardson extrapolation in space was originally developed by Tadjeran et al. to recover second-order accuracy in space and time (J. Comput. Phys., 2006).
 - A Eulerian-Lagrangian method for space-fractional advection-diffusion equation (K. Wang & W., Adv. Water Resources, 2011)
 - Finite and finite volume methods (W. & Du, J. Comput. Phys., 2013).

$$\frac{\partial u(x, y, t)}{\partial t} - d_{+}(x, y, t) \frac{\partial^{\alpha} u(x, y, t)}{\partial_{+} x^{\alpha}} - d_{-}(x, y, t) \frac{\partial^{\alpha} u(x, y, t)}{\partial_{-} x^{\alpha}} \\
-e_{+}(x, y, t) \frac{\partial^{\beta} u(x, y, t)}{\partial_{+} y^{\beta}} - e_{-}(x, y, t) \frac{\partial^{\beta} u(x, y, t)}{\partial_{-} y^{\beta}} = f(x, y, t), \\
(x, y) \in \Omega, \quad 0 < t \le T, \\
u(x, y, t) = u_{D}(x, y, t), \quad (x, y) \in \partial\Omega, \quad t \in [0, T], \\
u(x, y, 0) = u_{o}(x, y), \quad (x, y) \in \overline{\Omega}.$$
(14)

Here $\Omega := (x_l, x_r) \times (y_l, y_r)$ is a rectangular domain. $1 < \alpha, \beta < 2$.

A two-dimensional finite difference method and its ADI scheme (Meerschaert et al., J. Comput. Phys., 2006)

$$\frac{u_{i,j}^{m} - u_{i,j}^{m-1}}{\Delta t} - \frac{d_{i,j}^{+,m}}{h_{1}^{\alpha}} \sum_{k=0}^{i+1} g_{k}^{(\alpha)} u_{i-k+1,j}^{m} - \frac{d_{i,j}^{-,m}}{h_{1}^{\alpha}} \sum_{k=0}^{N_{1}-i+2} g_{k}^{(\alpha)} u_{i+k-1,j}^{m} \\
- \frac{e_{i,j}^{+,m}}{h_{2}^{\beta}} \sum_{l=0}^{j+1} g_{j}^{(\beta)} u_{i,j-l+1}^{m} - \frac{e_{i,j}^{-,m}}{h_{2}^{\beta}} \sum_{k=0}^{N_{2}-i+2} g_{l}^{(\beta)} u_{i,j+l-1}^{m} = f_{i,j}^{m}, \quad (15)$$

$$1 \le i \le N_{1}, \quad 1 \le j \le N_{2}, \quad m = 1, 2, \dots, M.$$
Let $N = N_{1}N_{2}$. Introduce N-dimensional vectors u^{m} and f^{m} defined by

$$u^{m} := \begin{bmatrix} u_{1,1}^{m}, \cdots, u_{N_{1},1}^{m}, u_{1,2}^{m}, \cdots, u_{N_{1},2}^{m}, \cdots, u_{1,N_{2}}^{m}, \cdots, u_{N_{1},N_{2}}^{m} \end{bmatrix}^{T},$$

$$f^{m} := \begin{bmatrix} f_{1,1}^{m}, \cdots, f_{N_{1},1}^{m}, f_{1,2}^{m}, \cdots, f_{N_{1},2}^{m}, \cdots, f_{1,N_{2}}^{m}, \cdots, f_{N_{1},N_{2}}^{m} \end{bmatrix}^{T}.$$
(16)

The finite difference method (15) can be expressed in the matrix form

$$(I + \Delta t A^m) u^m = u^{m-1} + \Delta t f^m.$$
(17)

For $m = 1, 2, \ldots, M$, at time step t^m :

1 solve the following equations in the x-direction (for each fixed y_j)

$$u_{i,j}^{m,*} - \frac{d_{i,j}^{+,m}\Delta t}{h_1^{\alpha}} \sum_{k=0}^{i+1} g_k^{(\alpha)} u_{i-k+1,j}^{m,*} - \frac{d_{i,j}^{-,m}}{h_1^{\alpha}} \sum_{k=0}^{N_1-i+2} g_k^{(\alpha)} u_{i+k-1,j}^{m,*}$$

$$= u_{i,j}^{m-1} + \Delta t f_{i,j}^m, \qquad 1 \le i \le N_1, \quad 1 \le j \le N_2,$$
(18)

2 solve the following equations in the *y*-direction (for each fixed x_i)

$$u_{i,j}^{m} - \frac{e_{i,j}^{+,m}\Delta t}{h_{2}^{\beta}} \sum_{l=0}^{j+1} g_{j}^{(\beta)} u_{i,j-l+1}^{m} - \frac{e_{i,j}^{-,m}\Delta t}{h_{2}^{\beta}} \sum_{k=0}^{N_{2}-i+2} g_{l}^{(\beta)} u_{i,j+l-1}^{m}$$

$$= u_{i,j}^{m,*}, \qquad 1 \le j \le N_{2}, \quad 1 \le i \le N_{1}.$$

$$(19)$$

Let $u_j^m := [u_{1,j}^m, u_{2,j}^m, \cdots, u_{N_1,j}^m]^T$ and $f_j^m := [f_{1,j}^m, \cdots, f_{N_1,j}^m]^T$. Then (18) are written as fully decoupled one-dimensional systems

$$(I_{N_1} + \Delta t A_j^{m,x}) u_j^{m,*} = u_j^{m-1} + \Delta t f_j^m, \qquad 1 \le j \le N_2.$$
(20)

Let $v_i^m := [u_{i,1}^m, u_{i,2}^m, \cdots, u_{i,N_2}^m]^T$ and $v_i^{m,*} := [u_{i,1}^m, u_{i,2}^m, \cdots, u_{i,N_2}^m]^T$ for $i = 1, \ldots, N_1$ be the rearrangements of u_j^m and $u_j^{m,*}$ for $j = 1, \ldots, N_2$. Then (21) can be rewritten as fully decoupled one-dimensional systems

$$(I_{N_2} + \Delta t B_i^{m,y}) v_i^m = v_i^{m,*}, \qquad 1 \le i \le N_1.$$
 (21)

- The ADI approach enables a direct application of the fast 1D solver to two- and three-dimensional space-fractional diffusion equations.
- The ADI approach does not need a direct decomposition of A^m .

A fast operator-splitting multistep ADI finite difference method (W. & K. Wang, J. Comput. Phys., 2011)

Theorem

The fast ADI method can be performed in $O(N \log^2 N)$ of operations per time step and requires $O(N \log N)$ of memory to store for two- and three-dimensional space-fractional diffusion equations.

An efficient storage of the fast ADI method requires the storage of the coefficient matrices $A_j^{m,x}$ for $j = 1, ..., N_2$ and $B_i^{m,y}$ for $i = 1, ..., N_1$. This requires $N_2O(N_1) + N_1O(N_2) = O(N)$ of memory. All the systems (20) can be solved in $N_2O(N_1 \log^2 N_1) = O(N \log^2 N)$ of operations, and those in (21) can be solved in $N_1O(N_2 \log^2 N_2) = O(N \log^2 N)$ of operations.

- The same result holds true for 3D problems.
- No multiple substeps needed if a conjugate-gradient type of iterative solver is used to solve the one-dimensional systems.

Two-dimensional numerical experiments

In the numerical experiments the data are given as follows

•
$$d_+(x, y, t) = d_-(x, y, t) = e_+(x, y, t) = e_-(x, y, t) = D = 0.005$$

•
$$f = 0, \ \alpha = \beta = 1.8, \ \Omega = (-1, 1) \times (-1, 1), \ [0, T] = [0, 1].$$

• The true solution is the fundamental solution to (14) expressed via the inverse Fourier transform

$$u(x, y, t) = \frac{1}{\pi} \int_0^\infty e^{-2D|\cos(\frac{\pi\alpha}{2})|(t+0.5)\xi^\alpha} \cos(\xi x) d\xi \times \frac{1}{\pi} \int_0^\infty e^{-2D|\cos(\frac{\pi\beta}{2})|(t+0.5)\eta^\beta} \cos(\eta y) d\eta.$$
(22)

- The initial condition $u_o(x,y)$ is chosen to be u(x,y,0).
- In the numerical experiments the Meerschaert & Tadjeran scheme and the fast ADI method were implemented using Matlab.

$h = \Delta t$	$ u_{FD} - u _{L^1}$	$ u_{FD} - u _{L^2}$	$\ u_{FD} - u\ _{L^{\infty}}$
2^{-4}	3.0281×10^{-2}	7.0346×10^{-2}	$5.7095 imes 10^{-1}$
2^{-5}	9.8231×10^{-3}	2.1051×10^{-2}	1.6409×10^{-1}
2^{-6}	3.9081×10^{-3}	7.3313×10^{-3}	5.5939×10^{-2}
2^{-7}	1.9647×10^{-3}	3.0910×10^{-3}	2.1663×10^{-2}
	$\ u_{FFD} - u\ _{L^1}$	$\ u_{FFD} - u\ _{L^2}$	$\ u_{FFD} - u\ _{L^{\infty}}$
2^{-4}	2.8115×10^{-2}	$6.1891 imes 10^{-2}$	4.8644×10^{-1}
2^{-5}	8.4583×10^{-3}	1.6793×10^{-2}	1.2472×10^{-1}
2^{-6}	3.1232×10^{-3}	5.2155×10^{-3}	3.6594×10^{-2}
2^{-7}	1.5340×10^{-3}	2.1439×10^{-3}	1.2013×10^{-2}

Table : The (normalized) L^1 , L^2 , and L^∞ errors of the fast ADI (FFD) method and traditional finite difference (FD) method with Gaussian elimination

$h = \Delta t$	CPU of finite difference (FD) with Gaussian elimination		
2^{-4}	49 s		
2^{-5}	$8.07 imes10^2$ s $=$ 13 m 27 s		
2^{-6}	$6.43 imes 10^4 \; { m s} = 17$ h 51 m		
2^{-7}	$5.90 imes 10^6~{ m s}=$ 1639 h 42 m $=$ 2 month and 8 days		
	CPU of the fast ADI finite difference method (FFD)		
2^{-4}	7.4 s		
2^{-5}	$63.6 \ s = 1 \ m \ 4 \ s$		
2^{-6}	$5.88 imes10^2~{ m s}=9$ m 48 s		
2^{-7}	$5.22 imes 10^3~{ m s}=1$ h 27 m		

Table : The consumed CPU of the fast ADI (FFD) method and the traditional finite difference (FD) method with Gaussian elimination.

Strength and weakness of ADI methods

- Strength: easy to implement
 - Numerical experiments show the utility of ADI methods.
 - ADI methods reduce the solution of multidimensional space-fractional diffusion equations to one-dimensional systems.
 - Avoid the relatively complex multidimensional coefficient matrix A^m .
- Weakness: restrictive
 - The ADI methods for space-fractional diffusion equations were proved to be unconditionally stable and convergent if the finite difference operators in the *x* and *y*-directions commute.
 - This condition is satisfied if $d_{\pm}(x,y,t)$ are independent of y and $e_{\pm}(x,y,t)$ are independent of x.

$$-D(K(x)(\theta_0 D_x^{-\beta} + (1-\theta)_x D_1^{-\beta})Du) = f(x), \quad x \in (0,1),$$

$$u(0) = u(1) = 0.$$
 (23)

• $2-\beta$ with $0<\beta<1$ represents the order of anomalous diffusion

- K is the diffusivity coefficient, $0 \le \theta \le 1$ indicates the relative weight of forward versus backward transition probability of the particles
- f is the source and sink term
- ${}_0D_x^{-\beta}u(x)$ and ${}_xD_1^{-\beta}u(x)$ are the left- and right-fractional integrals

$$\begin{cases} {}_{0}D_{x}^{-\beta}u(x) := \frac{1}{\Gamma(\beta)} \int_{0}^{x} (x-s)^{\beta-1}u(s)ds, \\ {}_{x}D_{1}^{-\beta}u(x) := \frac{1}{\Gamma(\beta)} \int_{x}^{1} (s-x)^{\beta-1}u(s)ds \end{cases}$$
(24)

 $\Gamma(\cdot)$ is the Gamma function

Analysis of an FDE with constant diffusivity (Ervin & Roop, NMPDE 2005)

• Galerkin formulation: given $f \in H^{-(1-\frac{\beta}{2})}(0,1)$, seek $u \in H_0^{1-\frac{\beta}{2}}(0,1)$

$$B(u,v) = \langle f, v \rangle, \qquad \forall \ v \in H_0^{1-\frac{\beta}{2}}(0,1).$$
(25)

Here $B: H_0^{1-\frac{\beta}{2}}(0,1)\times H_0^{1-\frac{\beta}{2}}(0,1)\to \mathbb{R}$ is defined to be

$$B(u,v) := \theta K \langle {}_{0}D_{x}^{-\beta}Du, Dv \rangle + (1-\theta)K \langle {}_{x}D_{1}^{-\beta}Du, Dv \rangle$$

= $\theta K ({}_{0}D_{x}^{1-\beta/2}u, {}_{x}D_{1}^{1-\beta/2}Dv)_{L^{2}(0,1)}$
+ $(1-\theta)K ({}_{x}D_{1}^{1-\beta/2}u, {}_{0}D_{x}^{1-\beta/2}v)_{L^{2}(0,1)}$

 $\langle\cdot,\cdot\rangle$ is the duality pair between $H^{-(1-\frac{\beta}{2})}(0,1)$ and $H^{1-\frac{\beta}{2}}_0(0,1).$

• For $\theta = 1/2$, $B(\cdot, \cdot)$ is symmetric. This problem reduces to fractional Laplacian which is well studied in harmonic analysis.

Analysis of an FDE with constant diffusivity (continued)

• The coercivity of $B(\cdot, \cdot)$ is derived as follows

$$B(u,u) = K ({}_{0}D_{x}^{1-\beta/2}u, {}_{x}D_{1}^{1-\beta/2}u)_{L^{2}(0,1)}$$

= $-\cos((1-\beta/2)\pi)K|u|_{H^{1-\beta/2}(0,1)}^{2}$
= $\cos(\beta\pi/2)K|u|_{H^{1-\beta/2}(0,1)}^{2}$.

Theorem

 $B(\cdot, \cdot)$ is coercive and continuous on $H_0^{1-\frac{\beta}{2}}(0,1) \times H_0^{1-\frac{\beta}{2}}(0,1)$. Hence, the Galerkin weak formulation (25) has a unique solution. Moreover,

$$||u||_{H^{1-\frac{\beta}{2}}(0,1)} \le (1/\alpha) ||f||_{H^{-(1-\frac{\beta}{2})}(0,1)}.$$

Galerkin finite element methods and their error estimates

• Let $S_h(0,1) \subset H_0^{1-\frac{\beta}{2}}(0,1)$ be the finite element space of piecewise polynomials of degree m-1. Find $u_h \in S_h(0,1)$ such that

$$B(u_h, v_h) = \langle f, v_h \rangle, \qquad \forall v_h \in S_h(0, 1).$$

• The optimal-order error estimate holds for $u \in H^m(0,1) \cap H_0^{1-rac{eta}{2}}(0,1)$

$$||u_h - u||_{L^2(0,1)} + h^{1-\frac{\beta}{2}} ||u_h - u||_{H^{1-\frac{\beta}{2}}(0,1)} \le Ch^m ||u||_{H^m(0,1)}.$$

- The analysis was extended to DG and spectral methods.
- All of the analysis requires K to be positive constant.

Extensions to variable-coefficient problems

- Variable-coefficient models were derived in applications. Can the previous analysis be extended to cover these problems?
- In the context of variable diffusivity K

$$B(u,v) = \theta \langle K_0 D_x^{-\beta} Du, Dv \rangle + (1-\theta) \langle K_x D_1^{-\beta} Du, Dv \rangle$$

$$\neq \theta \langle K Du, {}_x D_1^{-\beta} Dv \rangle + (1-\theta) \langle K Du, {}_0 D_x^{-\beta} Dv \rangle$$

$$\neq \left(K_0 D_x^{-\beta/2} Du, {}_x D_1^{-\beta/2} Dv \right)_{L^2(0,1)}$$

• Each corresponds to a fractional equation of a different form

$$-D(KD^{1-\beta}u) \neq -D^{1-\beta}(KDu) \neq -D^{1-\beta/2}(KD^{1-\beta/2}u).$$

• The last form seems to be mathematically preferred, but still cannot guarantee its coercivity

$$(K_0 D_x^{-\beta/2} Du, {}_x D_1^{-\beta/2} Du)_{L^2(0,1)} \not\geq K_{min} ({}_0 D_x^{-\beta/2} Du, {}_x D_1^{-\beta/2} Du)_{L^2(0,1)} = \cos (\beta \pi/2) K_{min} |u|_{H^{1-\beta/2}(0,1)}^2.$$

There exist a K(x) consisting of two positive constants and a function $w \in H_0^{1-\frac{\beta}{2}}(0,1)$ such that B(w,w) < 0.

Let K(x) and $w \in H^1_0(0,1) \subset H^{1-rac{eta}{2}}_0(0,1)$ be defined by

$$K(x) := \begin{cases} K_l, & x \in (0, 1/2), \\ 1, & x \in (1/2, 1). \end{cases}$$

$$w(x) := \begin{cases} 2x, & x \in (0, 1/2], \\ 2(1-x), & x \in [1/2, 1). \end{cases}$$

Direct calculation gives

$${}_{0}D_{x}^{1-\beta}w(x) = \begin{cases} \frac{2x^{\beta}}{\Gamma(\beta+1)}, & x \in (0, 1/2), \\ \frac{2(x^{\beta}-2(x-1/2)^{\beta})}{\Gamma(\beta+1)}, & x \in (1/2, 1). \end{cases}$$

Then we have

$$B(w,w) = \frac{2^{1-\beta}}{\Gamma(\beta+2)} \Big(K_l - (2^{\beta+1} - 3) \Big).$$

Since $0 < \log_2 3 - 1 < 1$, choose $\log_2 3 - 1 < \beta < 1$ so that $2^{\beta+1} - 3 > 0$. Then we select $K_l > 0$ sufficiently small such that $K_l - (2^{\beta+1} - 3) < 0$. For such K and w, we have B(w, w) < 0.

Characterization of the solution to fractional equations

- Consider a one-sided problem (problem (23) with $\theta = 1$)
 - $-D(K(x) \ _0D_x^{-\beta}Du) = f(x), \ x \in (0,1), \ u(0) = u(1) = 0.$ (26)
- mass balance of a fractional Darcy's law, physically reasonable

Theorem

Assume that $K \in C^{1,\alpha}[0,1]$ and $f \in C^{\alpha}[0,1]$. Then u is the unique solution to (26) if and only if it can be expressed as

$$u = {}_{0}D_{x}^{\beta}w_{f} - {}_{0}D_{1}^{\beta}w_{f} ({}_{0}D_{1}^{\beta}w_{b})^{-1}{}_{0}D_{x}^{\beta}w_{b},$$
(27)

where w_f and w_b are the solutions to the following problems

$$-D(K(x)Dw_f) = f, \quad x \in (0,1); \qquad w_f(0) = w_f(1) = 0, -D(K(x)Dw_b) = 0, \quad x \in (0,1); \qquad w_b(0) = 0, \quad w_b(1) = 1.$$
(28)

A Petrov-Galerkin weak formulation

- For a constant diffusivity coefficient K, the Galerkin formulation is coercive on the product space $H_0^{1-\beta/2}(0,1) \times H_0^{1-\beta/2}(0,1)$.
- In the context of a variable diffusivity coefficient K
 - The Galerkin formulation is *not* coercive on any product space $H \times H$.
 - A physically reasonable equation is expressed as the divergence of a fractional diffusive flux of order 1β .
 - We propose a Petrov-Galerkin formulation imposed on $H_0^{1-\beta}(0,1) \times H_0^1(0,1)$: Seek $u \in H_0^{1-\beta}(0,1)$ such that

$$A(u,v) := \int_0^1 K(x) \ _0 D_x^{1-\beta} u Dv dx = \langle f, v \rangle, \quad \forall v \in H_0^1(0,1)$$
 (29)

- Even for constant K, the Petrov-Galerkin formulation is different from the Galerkin formulation
 - The latter is defined on $H_0^{1-\beta/2}(0,1)\times H_0^{1-\beta/2}(0,1)$ for any given $f\in H^{-(1-\beta/2)}(0,1)$
 - The former is defined on $H^{1-\beta}_0(0,1)\times H^1_0(0,1)$ for any given $f\in H^{-1}(0,1).$

Theorem

Assume $0 \le \beta < 1/2$ and $0 < K_{min} \le K \le K_{max} < \infty$. The bilinear form A(w, v) is weakly coercive

$$\inf_{w \in H_0^{1-\beta}(0,1)} \sup_{v \in H_0^1(0,1)} \frac{A(w,v)}{\|w\|_{H^{1-\beta}(0,1)} \|v\|_{H^1(0,1)}} \ge \gamma(\beta) > 0,
\sup_{w \in H_0^{1-\beta}(0,1)} A(w,v) > 0 \quad \forall \ v \in H_0^1(0,1) \setminus \{0\}.$$
(30)

Thus, the Petrov-Galerkin formulation (29) has a unique weak solution $u \in H_0^{1-\beta}(0,1)$. Furthermore,

$$\|u\|_{H^{1-\beta}(0,1)} \le \frac{K_{max}}{\gamma} \|f\|_{H^{-1}(0,1)}.$$
(31)

Thank You!

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