Tempered fractional calculus

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1. Introduction

Fractional derivatives were invented by Leibnitz soon after the more familiar integer order derivatives [38,52], but have only recently become popular in applications. They are now used to model a wide variety of problems in physics [24,35,38,50,51,55,65], finance [23,27,37,42,60,61], biology [2,4,22,26,36], and hydrology [1,7,8,15,17,62]. Fractional derivatives can be most easily understood in terms of their connection to probability [45,46]. Einstein [20] explained the connection between random walks, Brownian motion, and the diffusion equation

\[
\partial_t p(x,t) = \partial^2_x p(x,t). \]

Sokolov and Klafter [63] review the modern theory of anomalous diffusion, where the integer order derivatives in the diffusion equation are replaced by their fractional analogues: \(\partial^\beta_t p(x,t) = \partial^\alpha_x p(x,t)\). A fractional space derivative of order \(\alpha < 2\) corresponds to heavy tailed power law particle jumps \(P[J > x] \approx x^{-\alpha}\) (the famous Lévy flight), while a fractional time derivative of order \(\beta < 1\) models heavy tailed power law waiting times \(P[W > t] \approx t^{-\beta}\) between jumps. Hence fractional space derivatives model anomalous super-diffusion, whereas a plume of particles spreads faster than the traditional diffusion equation predicts, and fractional time derivatives model anomalous sub-diffusion.

The goal of this paper is to describe a new variation on the fractional calculus, where power laws are tempered by an exponential factor. This exponential tempering has both mathematical and practical advantages. Mantegna and Stanley

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[40] proposed a truncated Lévy flight to capture the natural cutoff in real physical systems. Koponen [29] introduced the tempered Lévy flight as a smoother alternative, without a sharp cutoff. Cartea and del-Castillo-Negrete [12] developed the tempered fractional diffusion equation that governs the probability densities of the tempered Lévy flight. Unlike the truncated model, tempered Lévy flights offer a complete set of statistical physics and numerical analysis tools. Random walks with exponentially tempered power law jumps converge to a tempered stable motion [13]. Probability densities of the tempered stable motion solve a tempered fractional diffusion equation that describes the particle plume shape [3], just like the original Einstein model for traditional diffusion. Tempered fractional derivatives are approximated by tempered fractional difference quotients, and this facilitates finite difference schemes for solving tempered fractional diffusion equations [3]. The tempered diffusion model has already proven useful in applications to geophysics [44,70,71] and finance [10,11]. In finance, the tempered stable process models price fluctuations with semi-heavy tails, resembling a pure power law at moderate time scales, but converging to a Gaussian at long time scales [5]. Since the anomalous diffusion eventually relaxes into a traditional diffusion profile at late time, this model is also called transient anomalous diffusion [71].

Kolmogorov [28] invented a new stochastic model for turbulence in the inertial range. Mandelbrot and Van Ness [39] pointed out that this stochastic process is the fractional derivative of a Brownian motion, and coined the name fractional Brownian motion. Fractional Brownian motion can exhibit a useful property called long range dependence, where correlations fall off like a power law with time lag. A new variation on this model, called tempered fractional Brownian motion, is the tempered fractional derivative of a Brownian motion [47]. Tempered fractional Brownian motion can exhibit semi-long range dependence, with correlations that fall off like a power law at moderate time scales, but then eventually become short-range dependent at long time scales. This extends the Kolmogorov model for turbulence to also include low frequencies, and in fact tempered fractional Brownian motion provides a time-domain stochastic process model for the famous Davenport spectrum of wind speed [6,16,25,53], which is used to design electric power generation facilities.

2. Tempered fractional diffusion

We begin by recalling the connection between random walks, Brownian motion, and the diffusion equation (see [46] for complete details). Given a random walk of mean zero particle jumps \( S(n) = X_1 + \cdots + X_n \), the Central Limit Theorem implies that \( n^{-1/2}S(nt) \to B(t) \) in distribution. The probability density \( p(x,t) \) of the Brownian motion limit \( B(t) \) solves the diffusion equation \( \partial_t p(x,t) = D \partial_x^2 p(x,t) \). This useful connection between Brownian motion, random walks, and the diffusion equation assumes finite variance particle jumps. Power law jumps with density \( f(x) = C \alpha x^{-\alpha-1} \) \( x \in [1/\alpha, \infty) \) for \( 1 < \alpha < 2 \) have a finite mean but an infinite variance. Subtract the mean, and apply the extended central limit theorem [46, Theorem 3.37] to get \( n^{-1/2}S(nt) \to A(t) \). Now the probability density \( p(x,t) \) of the \( \alpha \)-stable Lévy motion \( A(t) \) solves the fractional diffusion equation \( \partial_t p(x,t) = D \partial_x^{\alpha} p(x,t) \).

Tempered fractional diffusion applies an exponential tempering factor to the particle jump density. Consider a random walk \( S^\varepsilon(n) \) with particle jump density

\[
f_{\varepsilon}(x) = C_{\varepsilon}^{-1} x^{-\alpha-1} e^{-\lambda_{\varepsilon} x} 1_{[\varepsilon, \infty)}(x)\quad \text{where } C_{\varepsilon} = \int_{\varepsilon}^{\infty} x^{-\alpha-1} e^{-\lambda_{\varepsilon} x} dx
\]

(1)

using the incomplete gamma function, and define the Poisson jump rate

\[
\lambda_{\varepsilon} = D \frac{\alpha}{\Gamma(1 - \alpha)} C_{\varepsilon}
\]

(2)

for any \( \varepsilon > 0 \). To ease notation, we begin with the case of positive jumps.

**Theorem 2.1.** Suppose \( 0 < \alpha < 1 \). Given a random walk \( S^\varepsilon(n) = X_1^\varepsilon + \cdots + X_n^\varepsilon \) with independent jumps, each having probability density function (1), and an independent Poisson process \( N_t^\varepsilon \) with rate (2), as \( \varepsilon \to 0 \) we have the convergence

\[
S^\varepsilon(N_t^\varepsilon) \Rightarrow A(t)
\]

(3)

where the limit is a tempered stable process whose probability density function \( p(x,t) \) has Fourier transform

\[
\hat{p}(k,t) = e^{-tD(\hat{\varepsilon} + ik)^\alpha - \lambda_{\varepsilon} t}
\]

(4)

for any \( t > 0 \).

**Proof.** The Poisson random variable satisfies \( P(N_t^\varepsilon = n) = e^{-\lambda_{\varepsilon} t} (\lambda_{\varepsilon} t)^n / n! \) for \( n \geq 0 \), and then

\[
P_{\varepsilon}(x,t) = P(S^\varepsilon(N_t^\varepsilon) \leq x) = \sum_{n=0}^{\infty} P(S^\varepsilon(n) \leq x | N_t^\varepsilon = n) \cdot P(N_t^\varepsilon = n)
\]

by the law of total probability. Apply the Fourier–Stieltjes transform \( \hat{f}(k) = \int e^{-ikx} f(dx) \) where \( f(x) = F'(x) \), noting that \( \hat{f}_{\varepsilon}(k)^\alpha \) is the Fourier transform of the probability distribution of \( S^\varepsilon(n) \), to get
\[ \hat{p}_\varepsilon(k, t) = \sum_{n=0}^{\infty} \hat{f}_\varepsilon(n) e^{-ik\varepsilon} \left( \frac{\lambda\varepsilon}{n!} \right)^n = e^{-\lambda\varepsilon(1-\hat{f}_\varepsilon(k))} \]  

(5)

Using the Taylor series for the complex exponential function. Rewrite this in the form

\[ \hat{p}_\varepsilon(k, t) = \exp \left[ t\varepsilon \int e^{-ikx} f_\varepsilon(x) \, dx \right] = \exp \left[ tD \frac{\alpha}{\Gamma(1-\alpha)} \int e^{-ikx} x^{-\alpha-1} e^{-\lambda x} \, dx \right]. \]

A straightforward computation using integration by parts and the formula for the gamma probability density [46, Eq. (3.14)] shows that

\[ (ik)^\alpha = \frac{\alpha}{\Gamma(1-\alpha)} \int_0^\infty (1 - e^{-ikx}) x^{-\alpha-1} \, dx \quad \text{for } 0 < \alpha < 1. \]

(6)

Use this formula twice to compute

\[ \frac{\alpha}{\Gamma(1-\alpha)} \int_0^\infty (e^{-ikx} - 1) e^{-\lambda x} x^{-\alpha-1} \, dx \]

\[ = \frac{\alpha}{\Gamma(1-\alpha)} \int_0^\infty (e^{-ik\lambda} - 1) x^{-\alpha-1} \, dx - \frac{\alpha}{\Gamma(1-\alpha)} \int_0^\infty (e^{-\lambda x} - 1) x^{-\alpha-1} \, dx \]

\[ = -[(\lambda + ik)^\alpha - \lambda^\alpha] \]

(7)

when \( 0 < \alpha < 1 \). Then as \( \varepsilon \to 0 \), we get

\[ \hat{p}_\varepsilon(k, t) \to \hat{p}(k, t) = e^{-tD[(\lambda + ik)^\alpha - \lambda^\alpha]} \]

for any \( t \geq 0 \). \( \square \)

It follows from Theorem 2.1 that \( \hat{p}(k, t) = e^{-tD[(\lambda + ik)^\alpha - \lambda^\alpha]} \) is the Fourier transform of the tempered Lévy flight \( A(t) \), a stochastic process with tempered power law jumps. We define the tempered fractional derivative \( \partial^{\alpha,\lambda}_x f(x) \) as the function with Fourier transform \( [(\lambda + ik)^\alpha - \lambda^\alpha] \hat{f}(k) \) when \( 0 < \alpha < 1 \). Note that

\[ \partial_t \hat{p}(k, t) = -D[(\lambda + ik)^\alpha - \lambda^\alpha] \hat{p}(k, t) \]

and invert the Fourier transform to see that the probability density \( p(x, t) \) of the tempered Lévy flight \( A(t) \) is the point source solution to the tempered fractional diffusion equation

\[ \partial_t p(x, t) = -D \partial^{\alpha,\lambda}_x p(x, t). \]

We will also define the negative tempered fractional derivative \( \partial^{\alpha,\lambda}_x f(x) \) as the function with Fourier transform \( [(\lambda - ik)^\alpha - \lambda^\alpha] \hat{f}(k) \) when \( 0 < \alpha < 1 \). A combination of positive and negative jumps with particle jump density

\[ f_\varepsilon(x) = C^{-1}_\varepsilon \left[ p x^{-\alpha-1} e^{-\lambda x} I_{(\varepsilon, \infty)}(x) + q |x|^{-\alpha-1} e^{-\lambda |x|} I_{(-\infty, -\varepsilon)}(x) \right] \]

(8)

for \( p, q \geq 0 \) with \( p + q = 1 \) leads to a tempered stable limit process \( A(t) \) having both positive and negative jumps. A simple extension of Theorem 2.1 shows that (3) holds, and now the limit density \( p(x, t) \) solves the tempered fractional diffusion equation

\[ \partial_t p(x, t) = -pD \partial^{\alpha,\lambda}_x p(x, t) - qD \partial^{\alpha,\lambda}_x p(x, t). \]

To write the tempered fractional derivative in real space, use the formula (7) to see that

\[ [(\lambda + ik)^\alpha - \lambda^\alpha] \hat{f}(k) = \frac{\alpha}{\Gamma(1-\alpha)} \int_0^\infty \left( \hat{f}(k) - e^{-iky} \hat{f}(k) \right) e^{-\lambda y} y^{-\alpha-1} \, dy \]

and then use the shift property \( \int e^{-ikx} f(x-y) \, dx = e^{-iky} \hat{f}(k) \) of the Fourier transform to see that

\[ \partial^{\alpha,\lambda}_x f(x) = \frac{\alpha}{\Gamma(1-\alpha)} \int_0^\infty \left( f(x) - f(x-y) \right) e^{-\lambda y} y^{-\alpha-1} \, dy \]

(9)
for $0 < \alpha < 1$. A similar argument shows that
\[ \tilde{a}v(\tilde{k})f(x) = \frac{\alpha}{\Gamma(1 - \alpha)} \int_0^\infty (f(x) - f(x + y))e^{-\lambda x}y^{\alpha - 1}dy. \] (10)

**Theorem 2.2.** Suppose $1 < \alpha < 2$. Given the mean-centered random walk $\beta(\alpha)$ with independent jumps, each having probability density function (1) and mean $\mu_\alpha = \alpha C^{1/\alpha}/(\alpha - 1)$, and an independent Poisson process $N_\varepsilon$ with rate (2), as $\varepsilon \to 0$ we have the convergence
\[ \beta(\alpha) - \beta(\alpha)\mu_\alpha \Rightarrow A(t) \]
where the limit is a mean zero tempered stable Lévy motion whose probability density function $p(x, t)$ has Fourier transform
\[ \hat{p}(k, t) = e^{-tD((\lambda + ik)\alpha - \lambda^\alpha - ik\lambda x^\alpha - 1)} \]
for any $t \geq 0$.

**Proof.** An easy computation shows that the jump variable $X_\varepsilon$ with probability density (1) has mean $\mu_\varepsilon = \int x f_\varepsilon(x) dx = \alpha C^{1/\alpha}/(\alpha - 1)$. Then it follows from (5) that the density of $\beta(\alpha) - \beta(\alpha)\mu_\alpha$ has Fourier transform
\[ \hat{p}_\varepsilon(k, t) = e^{-\lambda, t(1 - x)}e^{-i k, x} \]
for any $t \geq 0$. Rewrite this in the form
\[ \hat{p}_\varepsilon(k, t) = \exp \left[ -\lambda, t \int_0^\infty \left( 1 - e^{-\lambda, x} + i k, x \right) f_\varepsilon(x) dx \right] \]
using the fact that $\Gamma(2 - \alpha) = (1 - \alpha)\Gamma(1 - \alpha)$. Use (6) and another integration by parts [46, p. 58] to see that
\[ \int (i k)^\alpha = \frac{\alpha(\alpha - 1)}{\Gamma(2 - \alpha)} \int_0^\infty \left( e^{-\lambda, x} - 1 + i k, x \right) \lambda^{\alpha - 1} dx \] for $1 < \alpha < 2$.

Let $C = \alpha(\alpha - 1)/\Gamma(2 - \alpha)$ and compute
\[ C \int_0^\infty \left( e^{-\lambda, y} - 1 + i k, y \right) e^{-\lambda, y}y^{\alpha - 1} dy = C \int_0^\infty \left( e^{-\lambda, y} - 1 + (\lambda + i k, y) \right) y^{\alpha - 1} dy = C \int_0^\infty \left( e^{-\lambda, y} - 1 + i k, y \right) y^{\alpha - 1} dy - C \int_0^\infty \left( e^{-\lambda, y} - 1 \right) i k, y y^{\alpha - 1} \]
using (13). Then as $\varepsilon \to 0$, we get
\[ \hat{p}_\varepsilon(k, t) \to \hat{p}(k, t) = e^{-tD((\lambda + ik)\alpha - \lambda^\alpha - ik\lambda x^\alpha - 1)} \]
for any $t \geq 0$. □

It follows from **Theorem 2.2** that $\hat{p}(k, t) = e^{-tD((\lambda + ik)\alpha - \lambda^\alpha - ik\lambda x^\alpha - 1)}$ is the Fourier transform of the tempered Lévy flight $A(t)$. We define the tempered fractional derivative $\tilde{a}^\alpha(\tilde{k})f(x)$ as the function with Fourier transform $\hat{a}^\alpha(\tilde{k})f(k)$ when $1 < \alpha < 2$. Since $\tilde{a}^\alpha(\tilde{k})f(k) = D((\lambda + ik)^\alpha - \lambda^\alpha - ik\lambda x^\alpha - 1)f(k)$, we can invert the Fourier transform to see that the probability density $p(x, t)$ of $A(t)$ is the point source solution to the tempered fractional diffusion equation
\[ \partial_t p(x, t) = D\tilde{a}^\alpha(\tilde{k})p(x, t). \] (15)

**Fig. 1** shows a typical particle path, illustrating the effect of tempering to cool the long particle jumps. To write these tempered fractional derivatives in real space, use the formula (14) to see that
\[ [(\lambda + ik)^\alpha - \lambda^\alpha - ik\lambda x^\alpha - 1]^{-1}f(k) = \frac{\alpha(\alpha - 1)}{\Gamma(2 - \alpha)} \int_0^\infty \left( e^{-\lambda, y} - 1 + i k, y \right) e^{-\lambda, y}y^{\alpha - 1} dy \]
Fig. 1. Tempered fractional diffusion particle paths with $\alpha = 1.2$, from [3], showing the effect of tempering on long particle jumps.

Fig. 2. Symmetric tempered stable model fit (solid line) with $\alpha = 1.1, \lambda = 1.2, D = 0.1$ to one-step bilinear ARMA forecast errors for annual inflation rates. The best fitting normal density (dashed line) fails to capture the sharp data peak.

The particle jump density (8) leads to a tempered stable limit process $A(t)$ having both positive and negative jumps. A simple extension of Theorem 2.2 shows that (11) holds, and now the limit density $p(x,t)$ solves the tempered fractional diffusion equation

$$\partial_t p(x,t) = pD \partial_{\alpha}^{\alpha} p(x,t) + qD \partial_{\alpha}^{\alpha} p(x,t).$$

If $p = q$ then this produces a symmetric profile, with semi-heavy tails. That is, the tails of the probability density $p(x,t)$ resemble a power law $p(x,t) \approx |x|^{-\alpha-1}$ for large $|x|$ and moderate $t > 0$, but as $t \to \infty$ the tails relax to a Gaussian profile. These semi-heavy tails are typical in applications to finance [10,11]. Fig. 2 fits a symmetric tempered stable density function to macroeconomic data on inflation rates. The data shows a sharper peak and a heavier tail than the best fitting Gaussian curve.

The tempered space-fractional diffusion equation models transient super-diffusion, where a particle plume initially spreads faster than the traditional diffusion equation predicts, but later relaxes to a typical diffusion profile. The corresponding model for transient sub-diffusion assumes tempered power law waiting times between particle jumps. Suppose
that the nth particle jump \( S(n) = X_1 + \cdots + X_n \) occurs at a random time \( T_n = W_1 + \cdots + W_n \) where \( W_n \) are all independent with density \( d(t) = B\beta t^{-\beta-1}e^{-\eta t}1_{[\beta,\infty)}(t) \) for some \( 0 < \beta < 1 \). Theorem 2.1 yields random walk convergence to another stable Lévy motion \( D_t \) with Laplace transform \( \tilde{g}(s,t) = e^{-t\psi(s)} \) where the Laplace symbol \( \psi(s) = (\eta + s)^\beta - \eta^\beta \). The number of jumps by time \( t > 0 \) is given by the renewal process \( N_t = \max(n \geq 0: T_n \leq t) \), the inverse of \( T_n \) (graph \( T_n \) versus \( n \), then swap the axes, to get the graph of \( N_t \) versus \( t \)). Then the CTRW (continuous time random walk) defined by \( S(N_t) \) gives the particle location at time \( t > 0 \).

A general result from CTRW limit theory [43, Theorem 2.1] shows that the CTRW converges at late time to \( A(E_t) \), a tempered Lévy flight with the time variable replaced by an independent inverse tempered stable subordinator \( E_t = \inf(u > 0: D_u \geq t) \). Since \( \mathbb{P}[E_t \leq u] = \mathbb{P}[D_u \geq t] \), we can take derivatives and then Laplace transforms to see that the density \( h(u,t) \) of \( E_t \) has Laplace transform

\[
\tilde{h}(u,s) = \int_0^\infty e^{-st}h(u,t)\,dt = s^{-1}\psi_D(s)e^{-u\psi_D(s)},
\]

see [43, Theorem 3.1] for details. Since \( x = A(u) \) has density function \( p(x,u) \) and \( u = E_t \) has density function \( h(u,t) \), the CTRW limit process \( A(E_t) \) has density

\[
q(x,t) = \int_0^\infty p(x,u)h(u,t)\,du.
\]

Recall that the tempered Lévy density has Fourier transform \( \hat{p}(k,u) = e^{-u\psi_A(k)} \) with Fourier symbol \( \psi_A(k) = pD[(\lambda + ik)^\alpha - \lambda^\alpha - i\kappa\lambda^{\alpha-1}] + qD[(\lambda - ik)^\alpha - \lambda^\alpha + i\kappa\lambda^{\alpha-1}] \) for \( 1 < \alpha < 2 \). Take Laplace and Fourier transforms to see that

\[
\tilde{q}(k,s) = \int_0^\infty \hat{p}(k,u)\tilde{h}(u,s)\,du = \frac{s^{-1}\psi_D(s)}{\psi_D(s) + \psi_A(k)},
\]

then rearrange and invert to see that the limit density solves the space–time tempered fractional diffusion equation

\[
\partial_t^{\beta,\eta} p(x,t) = pD\partial_x^{\alpha,\lambda} p(x,t) + qD\partial_x^{\alpha,\lambda} p(x,t) + \delta(x)f(t)
\]

(18)

where the forcing term \( f(t) = \delta(t,\infty) \) has Laplace transform \( \tilde{f}(s) = s^{-1}\psi_D(s) \), see [43, Theorem 4.1] for complete details. If \( \eta = 0 \), the boundary term reduces to \( f(t) = t^{\beta-1}/\Gamma(1-\beta) \), as in the fractional kinetic equation of Zaslavsky [69]. Tempered jumps are the basis for the popular CGMY model in finance [10,11]. Tempered waiting times were applied to problems in ground water hydrology [44], and tempering in both variables was used for sediment transport in rivers [71]. Tempered fractional diffusion was first proposed by Cartea and del-Castillo-Negrete [12], and developed further in [3,44], see also [46, Sections 7.2 and 7.3]. A more general tempering scheme was developed in [13]. The theory of tempered stable processes was developed by Rosiński [57], and an exact simulation scheme for the sample paths of a tempered Lévy flight was presented in Cohen and Rosiński [14].

3. Tempered fractional calculus

Given any \( \lambda > 0 \), we define the positive tempered fractional integral of a suitable function \( f(x) \) by

\[
\int_+^{\alpha,\lambda} f(x) = \frac{1}{\Gamma(\alpha)} \int_{-\infty}^x f(u)(x-u)^{\alpha-1}e^{-\lambda(x-u)}\,du,
\]

(19)

and the negative tempered fractional integral by

\[
\int_-^{\alpha,\lambda} f(x) = \frac{1}{\Gamma(\alpha)} \int_x^\infty f(u)(u-x)^{\alpha-1}e^{-\lambda(u-x)}\,du.
\]

(20)

If \( \lambda = 0 \), these formulæ reduce to the well-known Riemann–Liouville fractional integrals [46,58]. Hence we will call these operators the Riemann–Liouville tempered fractional integrals. Since these operators are convolutions, their Fourier transforms are products. Since \( g(x) = x^\alpha e^{-\lambda x}1_{[0,\infty)}(x)/\Gamma(\alpha) \) has Fourier transform \( \hat{g}(k) = (\lambda + ik)^{-\alpha} \), it follows from the convolution property of the Fourier transform that \( \int_+^{\alpha,\lambda} f(x) \) has Fourier transform \( (\lambda + ik)^{-\alpha} \hat{f}(k) \). Likewise \( \int_-^{\alpha,\lambda} f(x) \) has Fourier transform \( (\lambda - ik)^{-\alpha} \hat{f}(k) \), and when \( \lambda = 0 \) we recover the well-known formulæ for the Fourier transform of a Riemann–Liouville fractional integral [58].
Fourier transform to the (untempered) fractional derivative easily that

\[ g \]

normalized tempered fractional derivative uniqueness of the Fourier transform implies that

where

\[ n \]

follows by another easy Fourier transform argument.

The space of rapidly decreasing functions \( \mathcal{S}(\mathbb{R}) \) consists of the infinitely differentiable functions \( f : \mathbb{R} \to \mathbb{R} \) such that

\[ \sup_{x \in \mathbb{R}} |x^n g^{(m)}(x)| < \infty, \]

where \( n, m \) are non-negative integers, and \( g^{(m)} \) is the derivative of order \( m \). The space of tempered distributions \( \mathcal{S}'(\mathbb{R}) \) consists of continuous linear functionals on \( \mathcal{S}(\mathbb{R}) \). The Fourier transform maps \( \mathcal{S}(\mathbb{R}) \) into itself. If \( f : \mathbb{R} \to \mathbb{R} \) is of polynomial growth, so that \( \int |f(x)| (1 + |x|)^{-p} dx < \infty \) for some \( p > 0 \), then \( \hat{T}_f(\varphi) = \int f(x) \varphi(x) dx := \langle f, \varphi \rangle \) is a tempered distribution, also called a generalized function, with Fourier transform \( \hat{T}_f(\varphi) = \langle f, \varphi \rangle = \langle \hat{f}, \hat{\varphi} \rangle = T_\varphi(\hat{f}) \) for \( \varphi \in \mathcal{S}(\mathbb{R}) \). See Yosida [67, Ch. VI] for more details. For any tempered distribution \( f \), the tempered fractional integral \( \partial_{\pm} f(x) \) exist as a convolution with the tempered distribution \( g(x) = x^{\alpha-1} e^{-\lambda x} 1_{[0,\infty)}(x) / \Gamma(\alpha) \). The same holds for Riemann–Liouville fractional integrals (the case \( \lambda = 0 \)), since \( g(x) = x^{\alpha-1} 1_{[0,\infty)}(x) / \Gamma(\alpha) \) is of polynomial growth. Since \( G(k) = (\lambda + ik)^\alpha \) is of polynomial growth, it is also a tempered distribution, and hence it follows from the Fourier inversion formula on \( \mathcal{S}'(\mathbb{R}) \) that \( G = \hat{g} \) for some tempered distribution \( g \in \mathcal{S}'(\mathbb{R}) \). Then we may define the Riemann–Liouville tempered fractional derivative of a tempered distribution as the convolution with this function. If \( n - 1 < \alpha < n \), we can also write \( (\lambda + ik)^\alpha \hat{f}(k) = \langle \hat{f}, (\lambda + ik)^\alpha \rangle \) for \( \alpha \), and inverting yields an alternative definition in terms of the Riemann–Liouville tempered fractional integral:

\[ \partial_{\pm} f(x) = \frac{d^\alpha_{\pm}}{dx^\alpha} f(x) \]

where \( D_{\pm}^{\alpha} f(x) = e^{-\lambda x} f(x)^{(n)} \) is a tempered derivative of integer order, defined by (23). There are many technical issues behind the fractional calculus of tempered distributions [58, Chapter 8], and it would be interesting to extend that theory for tempered fractional calculus.
4. Tempered fractional Brownian motion

As noted in Section 2, a random walk \( S(n) = X_1 + \cdots + X_n \) with mean zero, finite variance particle jumps converge to a Brownian motion \( B(t) \). For this Gaussian stochastic process, \( B(0) = 0 \), \( B(t+s) - B(t) \) is independent of \( B(s) \) (independent increment property) and \( B(t+s) - B(s) \) is independent of \( B(s) \) (independent increment property). The stochastic integral \( \int f(x)B(dx) \) is defined for any \( f \in L^2(\mathbb{R}) \) as a Gaussian random variable with mean zero and variance \( \langle f, f \rangle = \int f(x)^2dx \), such the Itô isometry holds: the stochastic integrals \( \int f(x)B(dx) \) and \( \int g(x)B(dx) \) have covariance \( \langle f, g \rangle = \int f(x)g(x)dx \). See [59] for more details. Then for any \( H > 0 \) and \( \lambda > 0 \) we can define the tempered fractional Brownian motion

\[
B_{H,\lambda}(t) := \int \left[ e^{-\lambda(t-x)}(t-x)^{H-1/2} - e^{-\lambda(0-x)}(0-x)^{H-1/2} \right] B(dx)
\]

where \((x) = 1_{[0,\infty)}(x)\), and \( 0^0 = 0 \). The Gaussian stochastic process (24) has mean zero, and its increments are stationary, but not independent. Using the fact that \( B(ct) \sim e^{\lambda t} B(ct) \) (same distribution), it is not hard to check that tempered fractional Brownian motion has a nice scaling property: \( B_{H,\lambda}(ct) \sim e^{\lambda t} B_{cH,\lambda}(t) \) for every \( c > 0 \). If \( \lambda = 0 \) and \( 0 < H < 1 \) (required to keep the integrand in \( L^2(\mathbb{R}) \) when \( \lambda = 0 \)), we get the fractional Brownian motion with Hurst index \( H \). Kolmogorov [28] proposed this process with \( H = 1/3 \) as a model for turbulence. Mandelbrot and Van Ness [39] established the connection between fractional Brownian motion and fractional calculus. Next we explain that connection in the tempered case.

Stochastic integrals with respect to Brownian motion can also be constructed using white noise theory. Heuristically, one writes \( \int f(x)B(dx) = \int f(x)W(x)dx \) where the white noise \( W(x) = B'(x) \) is the (weak) derivative of the Brownian motion. This integral does not exist path-wise, since the paths of a Brownian motion are not differentiable. However, we can define \( W(f) := \int f(x)W(x)dx = (f, W) \) as a random distribution (generalized function) on \( L^2(\mathbb{R}) \) by specifying that this object has the Gaussian distribution and covariance function as \( \int f(x)B(dx) \) [30]. Taking \( f(x) = 1_{[0,1]}(x) \), it follows that \( B(t) = \int_0^t W(x)dx \), and in this sense, the white noise \( W(x) \) is the (distributional) derivative of \( B(x) \). Suppose that \( H > 1/2 \), and compute

\[
1_{[0,1]}^{H-1/2,\lambda} 1_{[0,1]}(x) = 1_{[0,1]}^{H-1/2,\lambda} W(x) = 1_{[0,1]}^{H-1/2,\lambda} W(x)
\]

for any \( t > 0 \). Using the fact that positive and negative Riemann–Liouville tempered fractional integrals are \( L^2(\mathbb{R}) \) adjoints, we can therefore use white noise theory to write

\[
B_{H,\lambda}(t) = \left\{ 1_{[0,1]}(x), 1_{[0,1]}^{H-1/2,\lambda} W(x) \right\}
\]

which shows that tempered fractional Brownian motion with \( H > 1/2 \) can be obtained by integrating a linear combination of tempered fractional integrals of a white noise. The same is true for \( 0 < H < 1/2 \), if we interpret the tempered fractional integral of negative order as a tempered fractional derivative, see [49] for more details. Now if we take \( \lambda = 0 \) and \( 0 < H < 1 \), we recover the fact that fractional Brownian motion is the fractional integral of a white noise [39,54].

Fractional Brownian motion with \( 1/2 < H < 1 \) is a popular model for long range dependence. The increments \( X_n = B_H(n) - B_H(n-1) \) form a stationary time series of Gaussian random variables with mean zero, and the covariance between \( X_n \) and \( X_{n+j} \) falls off like \( j^{2H-2} \) as \( j \to \infty \) [59, Proposition 7.2.10]. Tempered fractional Brownian motion with a small tempering parameter \( \lambda = 0 \) exhibits semi-long range dependence. The increments \( X_n = B_{H,\lambda}(n) - B_{H,\lambda}(n-1) \) form a stationary Gaussian time series, the covariance between \( X_n \) and \( X_{n+j} \) falls off like \( j^{2H-2} \) for moderate values of \( j \), but then tempering makes the covariance fall off faster (short range dependence) as \( j \) goes to infinity. When \( 0 < H < 1/2 \), both processes exhibit negative dependence, with a negative covariance between \( X_n \) and \( X_{n+j} \) for all \( j \) sufficiently large. See [47] for further details.

5. Tempered fractional difference operator

Tempered fractional derivatives can also be defined as the limit of a tempered fractional difference quotient.

**Theorem 5.1.** If \( f \) and its derivatives up to order \( n + \alpha \) exist and are absolutely integrable, then the Riemann–Liouville tempered fractional derivative

\[
\Delta_{+}^{\alpha,\lambda} f(x) = \lim_{h \to 0} h^{-\alpha} \Delta_{+}^{\alpha} f(x)
\]

where

\[
\Delta_{+}^{\alpha} f(x) = \sum_{j=0}^{\infty} w_j e^{-\lambda j} f(x - jh) \quad \text{with} \quad w_j := (-1)^j \binom{\alpha}{j} \frac{(1 + \alpha)}{j! \Gamma(1 + \alpha - j)}.
\]
Proof. The proof is similar to [46, Proposition 2.1]. The fractional binomial formula
\[ \sum_{k=0}^{\infty} \binom{\alpha}{k} e^{zk} = (1 + z)^\alpha \]
holds for any \( \alpha > 0 \) and any complex \( |z| \leq 1 \). Since \( e^{-ikjh} \hat{f}(k) \) is the Fourier transform of \( f(x - jh) \), the Fourier transform of \( h^{-\alpha} \Delta_+^\alpha f(x) \) is
\[ h^{-\alpha} \sum_{j=0}^{\infty} (-1)^j \binom{\alpha}{j} e^{-\lambda jh} e^{-ikjh} \hat{f}(k) \]
\[ = h^{-\alpha} \sum_{j=0}^{\infty} \binom{\alpha}{j} (-1)^j e^{-\lambda(j+1)h} \hat{f}(k) \]
\[ = h^{-\alpha} \left(1 - e^{-\lambda(h+1)}\right)^\alpha \hat{f}(k) \rightarrow (\lambda + ik)^\alpha \hat{f}(k) \]
as \( h \to 0 \), using a Taylor expansion of the complex exponential function. Since \( f \) and its derivatives up to order \( n > 1 + \alpha \) exist and are absolutely integrable, we have \( \hat{f}(k) \leq C/(1 + |k|^n) \) for some \( C > 0 \) [46, Lemma 2.4], and so \( |(\lambda + ik)^\alpha \hat{f}(k)| \leq C(\lambda^2 + k^2)^{\alpha/2}/(1 + |k|^n) \). Hence \((\lambda + ik)^\alpha \hat{f}(k)\) is absolutely integrable, and then the inversion formula for the Fourier transform [46, Theorem 1.4] implies that there exists a function \( \Delta_+^\alpha f(x) \) with this Fourier transform. Then the continuity theorem for the Fourier transform [46, Theorem 1.3] implies that (25) holds. \( \square \)

The tempered fractional difference quotient can be applied to develop simple, effective numerical schemes to solve the tempered fractional diffusion equation. For physical reasons [7,8,17,62], the most important case in applications is \( 1 < \alpha < 2 \). Consider the tempered fractional diffusion equation with drift
\[ \partial_\alpha \partial_\lambda p(x, t) = -v(x) \partial_{\lambda,\lambda} p(x, t) + D(x) \partial_\alpha \partial_\lambda p(x, t) + f(x, t) \] (26)
where \( 1 < \alpha \leq 2 \), \( v(x) \geq 0 \), and \( D(x) \geq 0 \) on a finite domain \( a \leq x \leq b \), with initial condition \( p(x, 0) = p_0(x) \), boundary conditions \( p(a, t) = 0 \) and \( p(b, t) = B(t) \), and forcing function \( f(x, t) \) for all \( t \geq 0 \). Using Theorem 5.1 along with (22) and the fact that \( h^{-\alpha} (1 - e^{-\lambda h})^\alpha f(x) \to \lambda^\alpha f(x) \) as \( h \to 0 \), it follows that
\[ \partial_\alpha^\alpha \partial_\lambda f(x) + \alpha \lambda^{-1} f'(x) = \lim_{h \to 0} h^{-\alpha} \sum_{j=0}^{\infty} (-1)^j \binom{\alpha}{j} e^{-\lambda jh} f(x - jh) - h^{-\alpha} (1 - e^{-\lambda h})^\alpha f(x). \]

To write the details of our numerical code, set \( t_i = i \Delta t \), \( x_j = a + j \Delta x \), \( h = \Delta x \), \( p_{ij} = p(x_j, t_i) \), \( D_j = D(x_j) \), \( v_j = v(x_j) + D_j \alpha \lambda^{-1} \), and \( f_{ij} = f(x_j, t_i) \). It is natural to consider the implicit Euler scheme
\[ p_{i+1, j} - p_{ij} = -v_{ij} p_{i+1, j} - p_{i+1, j-1} + D_j h^{-\alpha} \sum_{m=0}^{j} g_m p_{i+1, j-m} + f_{ij} \Delta t \]
using the weights
\[ g_j = \begin{cases} w_{j} e^{-jh\lambda} & \text{for } j \geq 1, \\ w_{j} e^{-jh\lambda} - (1 - e^{-h\lambda})^\alpha & \text{for } j = 0. \end{cases} \]

However, this implicit scheme is unstable. The proof is very similar to [41, Proposition 2.3]. The explicit Euler scheme (replace \( i + 1 \) by \( i \) on the right-hand side) is also unstable. The proof is essentially identical to [41, Proposition 2.1].

In order to obtain a stable convergent numerical method, it is necessary to use a shifted finite difference approximation
\[ \partial_\alpha^\alpha \partial_\lambda f(x) + \alpha \lambda^{-1} f'(x) = \lim_{h \to 0} h^{-\alpha} \sum_{j=0}^{\infty} g_j f(x - (j - 1)h), \] (27)
where the exponentially tempered Grünwald weights are defined by
\[ g_j = \begin{cases} w_{j} e^{-(j-1)h\lambda} & \text{for } j \neq 1, \\ w_{1} e^{h\lambda} (1 - e^{-h\lambda})^\alpha & \text{for } j = 1. \end{cases} \] (28)
The proof that (27) holds is similar to Theorem 5.1, see [3, Proposition 3] for details. Now consider the implicit Euler scheme
\[ p_{i+1, j} - p_{ij} = -v_{ij} p_{i+1, j} - p_{i+1, j-1} + D_j h^{-\alpha} \sum_{m=0}^{j+1} g_{m+1} p_{i+1, j-m+1} + f_{ij} \Delta t. \] (29)
Theorem 5.2. The implicit Euler scheme (29) for the tempered fractional diffusion equation (26) using the weights (28) is consistent and unconditionally stable.

Proof. The proof is similar to [41, Theorem 2.7]. The main difference is that the Grünwald weights $w_j$ are replaced by the tempered weights $g_j$. It follows from the fractional binomial formula that
\[
\sum_{j=0}^{\infty} g_j = e^{\beta} \sum_{j=0}^{\infty} (-1)^j \frac{\alpha j}{j!} e^{-\beta j} - e^{\beta} (1 - e^{-\beta})^\alpha = 0,
\]
and hence this numerical method mass-preserving. Since $1 < \alpha < 2$ we have $w_1 = -\alpha$ and $w_j > 0$ for all $j \neq 1$, so that $g_1 < 0$ and $g_j > 0$ for all $j \neq 1$. Then
\[
\sum_{j=0}^{K} g_j < 0
\]
for any finite number $K$. The implicit Euler scheme can be written as a linear system of equations $AP_{i+1} = P_i + F_i \Delta t$ in matrix form where $P_i = [p_{i,0}, \ldots, p_{i,N}']'$, $F_i = [f_{i,0}, \ldots, f_{i,N}']'$, $N = (b - a)/h$, and the inequality $\sum_{j=0}^{K} g_j < 0$ implies that every eigenvalue $\zeta$ of the implicit iteration matrix $A$ satisfies $|\zeta| > 1$. Hence the spectral radius of the inverse matrix $\rho(A^{-1}) \leq 1$, and the result follows. \( \square \)

Note that the shifted finite difference approximation (27) is essentially a convolution with the exponentially tempered Grünwald weights. An application of Stirling’s formula shows that $\Gamma(\alpha) = \sqrt{2\pi} (\alpha/e)^\alpha (1 + O(1/\alpha))$ as $\alpha \to \infty$, and this connects the finite difference scheme (29) with the probability model from Section 2. In the probability model, the tempered fractional derivative codes power law jumps with density function $f(x) \propto x^{\alpha-1} e^{-x}$ for large $x$. In the finite difference approximation of the tempered fractional derivative, the particle flux into location $x$ from location $x - jh$ follows the same tempered power law model. Between time $t_i$ and time $t_i + \Delta t$, the mass at location $x_j$ is reduced by an amount proportional to the current particle mass density $p(x_j, t_i)$ at this location, and increased by an amount proportional to the mass at other locations $x_j - m \Delta x$ with a weight $g_m = w_m e^{-j \Delta x}$ that falls off like a tempered power law with distance $m \Delta x$.

Example 5.3. Consider the tempered fractional diffusion equation (26) with $v(x) = 0$, $x \in [0, 1]$, $\alpha = 1.5$, $\lambda = 0.5$, initial condition $u(x, 0) = x^{0.5} e^{-x^2} / \Gamma(\beta + 1)$ with $\beta = 2.5$, diffusion coefficient $c(x) = x^{\beta} / \Gamma(\beta + 1)$, forcing function
\[
q(x, t) = e^{-\lambda x^2} \Gamma(\beta + 1) \left( \frac{1 - \alpha}{\Gamma(\beta + 1)} + \frac{\alpha \lambda^{1-\alpha} x^{\alpha-1}}{\Gamma(\beta + 1)} \right) - \frac{2x^\beta}{\Gamma(1 + \beta - \alpha)}
\]
and boundary conditions $u(0, t) = 0$ and $u(1, t) = B(t) := e^{-\lambda t} / \Gamma(\beta + 1)$. The exact solution is given by $u(x, t) = x^{\beta} e^{-\lambda x^2} / \Gamma(1 + \beta)$. A similar example was considered in [3, Example 7]. Set $F_i = [f_{i1}, \ldots, f_{iN-2}, f_{iN-1} + D_{N-1} \Delta t g_i]'$, $p_{i0} = 0$, $p_{i,N} = B(t_i)$, and let $\hat{A}$ denote the $(N-1) \times (N-1)$ matrix with entries
\[
\hat{A}_{ij} = \begin{cases} 1 + v_i h^{-1} \Delta t - D_i h^{-\alpha} \Delta t g_1 & \text{when } j = i, \\ v_i h^{-1} \Delta t - D_i h^{-\alpha} \Delta t g_2 & \text{when } j = i - 1, \\ -v_i h^{-1} \Delta t - D_i h^{-\alpha} \Delta t g_{i-1} & \text{when } j < i - 1 \text{ or } j = i + 1, \\ 0 & \text{otherwise}. \end{cases}
\]
Then the vector of interior points $\hat{P}_i = [p_{i,1}, \ldots, p_{i,N-1}]'$ solves the iteration equation $\hat{A} \hat{P}_{i+1} = \hat{P}_i + \hat{F}_i \Delta t$. The additional term in the last entry of $\hat{F}_i$ accounts for cutting off the super-diagonal entry of the full iteration matrix $A$. The algorithm was implemented in MATLAB (code is available from the authors upon request), see Table 1 for a summary of results.

The implicit Euler method in Theorem 5.2 has error $O(\Delta x + \Delta t)$, consistent with Table 1. A Crank–Nicolson method for solving the tempered fractional diffusion equation (26) with $1 < \alpha \leq 2$ is developed in [3]. The method is stable and consistent, and second order convergent in time. However, because the finite difference approximation (27) is only first order accurate, the method is $O(\Delta t^2 + \Delta x^2)$. An application of Richardson extrapolation yields $O(\Delta t^2 + \Delta x^2)$, see [3] for more details. It is also possible to construct particle tracking solutions based on the Monte Carlo simulation scheme in [3, Section 4], see [44,71]. A wide variety of effective numerical methods have been developed to solve fractional diffusion equations, see for example [18,21,32–34,56,64,68]. It would certainly be interesting to extend these methods to tempered fractional diffusion equations. Even in the untempered case, many interesting open problems remain, including a rigorous proof that fractional boundary value problems are well-posed, see [19] for a nice discussion.
6. ARTFIMA model

Another useful application of the fractional difference operator arises in time series analysis. Given a sequence of independent Gaussian random variables $Z_n$ with mean zero and variance $\sigma^2$ (white noise sequence), a fractional noise sequence can be constructed by setting

$$X_n = \Delta^{-\alpha} Z_n = \sum_{j=0}^{\infty} (-1)^j \binom{-\alpha}{j} Z_n-j$$

where typically $-1/2 < \alpha < 1/2$. Since $\Delta^\alpha \Delta^\beta = \Delta^{\alpha+\beta}$ in general (this follows from the fractional binomial formula), one can also write $Z_n = \Delta^\alpha X_n$. Since the fractional difference is the discrete analogue of the fractional derivative, a fractional noise is closely related to fractional Brownian motion. Indeed, the sum $X_1 + \cdots + X_t \approx B_H(t)$ when $H + \alpha = 1/2$. More precisely, we have

$$n^{-H}(X_1 + \cdots + X_{[nt]}) \Rightarrow B_H(t) \text{ as } n \to \infty$$

for all $t > 0$, see [66, Theorem 4.6.1]. The fractional noise can also exhibit long range dependence. The covariance between $X_t$ and $X_{t+h}$ falls off like $|j|^{2H-2}$ as $j \to \infty$. In applications, a fractional difference is applied to a time series data set, and the order $\alpha$ of the fractional difference is chosen to remove long range correlations from the data. See [48] for a recent application to groundwater hydrology.

Fractional differencing can be combined with the standard ARMA($p, q$) model for time series, to yield the ARFIMA($p, \alpha, q$) time series model. The ARMA($p, q$) model is

$$X_t - \sum_{j=1}^{p} \phi_j X_{t-j} = Z_t + \sum_{i=1}^{q} \theta_i Z_{t-i}$$

and we say that $X_t$ follows an ARFIMA($p, \alpha, q$) if $\Delta^\alpha X_t$ follows an ARMA($p, q$) model. The spectral density $f_X(k)$ of a stationary time series $X_t$ is the discrete Fourier transform of its covariance function. If $\gamma(h)$ is the covariance between $X_t$ and $X_{t+h}$, the spectral density

$$f_X(k) = \frac{1}{2\pi} \sum_{j=-\infty}^{+\infty} e^{ikj} \gamma(j).$$

The spectral density of the noise sequence $Z_n$ is a constant $f_Z(k) = \sigma^2/(2\pi)$, which is the reason for the term “white noise,” as all frequencies have equal weight. Using the backward shift operator notation $BX_t = X_{t-1}$, one can write the ARMA($p, q$) model in the compact form $\Phi(B) X_t = \Theta(B) Z_t$, where $\Phi(z) = 1 - \phi_1 z - \cdots - \phi_p z^p$ and $\Theta(z) = 1 + \theta_1 z + \cdots + \theta_q z^q$. Then it follows from the theory of linear filters that the spectral density of an ARMA($p, q$) time series is given by

$$f_X(k) = \frac{\left|\Theta(e^{-ik})\right|^2}{\left|\Phi(e^{-ik})\right|^2} f_Z(k)$$

using the complex absolute value. Indeed, for any time invariant linear filter $X_t = \sum_j \psi_j Z_{t-j}$ a standard argument shows that $f_X(k) = |\Psi(e^{-ik})|^2 f_Z(k)$ where $\Psi(z) = \sum_j \psi_j z^j$, see for example [9]. For an ARMA($p, q$) time series, the filter function is $\Psi(z) = \Theta(z)/\Phi(z)$. Since

$$\Delta^\alpha = \sum_{j=0}^{\infty} (-1)^j \binom{\alpha}{j} B^j = (1-B)^\alpha$$

in operator notation, a similar argument shows that the spectral density of an ARFIMA($p, \alpha, q$) time series is given by

$$f_X(k) = \sigma^2 \left|\Theta(e^{-ik})\right|^2 2\pi |\Phi(e^{-ik})|^2 |1 - e^{-ik}|^{-2\alpha}.$$
As \( k \to 0 \), the fractional term \( |1 - e^{-ik}|^{-2\alpha} \sim |k|^{-2\alpha} \) blows up at a power law rate. This diverging spectral density is the hallmark of long range dependence. The tempered fractional difference

\[
X_t = \Delta^\alpha_t Z_t = \sum_{j=0}^{\infty} (-1)^j \binom{\alpha}{j} e^{-\lambda j} Z_{t-j}
\]

can provide a more flexible model for (semi-)long range dependence. We say that \( X_t \) follows an ARTFIMA(\( p, \alpha, \lambda, q \)) if \( \Delta^\alpha_t X_t \) follows an ARMA(\( p, q \)) model. Since

\[
\Delta^\alpha_t = \sum_{j=0}^{\infty} (-1)^j \binom{\alpha}{j} e^{-\lambda j} B^j = (1 - e^{-\lambda B})^\alpha
\]

in operator notation, it follows that the spectral density of an ARTFIMA(\( p, \alpha, \lambda, q \)) time series is given by

\[
f_X(k) = \frac{\sigma^2 |\Theta(e^{-ik})|^2}{2\pi |\Phi(e^{-ik})|^2} |1 - e^{-(\lambda + ik)}|^{-2\alpha}. \tag{30}
\]

For small values of the tempering parameter \( \lambda \approx 0 \), this spectral density grows like a power law as \( k \) decreases, but then remains bounded as \( k \to 0 \) because of tempering. More details on ARTFIMA(\( p, \alpha, \lambda, q \)) time series will be included in a forthcoming paper by the authors.

7. Turbulence

Kolmogorov [28] invented fractional Brownian motion as a model for turbulence in the inertial range. The main idea is that the spectral density grows like a power law as the frequency decreases, and a scaling argument leads to \( H = 1/3 \). This anti-persistent model has been verified in many real world experiments, for a range of frequencies. Davenport [16] modified this model in his study of wind speed at low altitudes, recognizing that the observed spectral density cannot actually diverge at low frequencies, outside the inertial range. The Davenport model for wind turbulence is \( s_t = \mu + X_t \) where \( \mu = \mathbb{E}[s_t] \) is the average wind speed, and the stochastic process \( X_t \) has the normalized spectral density

\[
4800DV_{10} \frac{x^2}{(1 + x^2)^{4/3}} \tag{31}
\]

where \( V_{10} \) is the mean velocity (m/s) at an altitude of 10 m, \( D \) is the corresponding drag coefficient, and \( x = 1200k/V_{10} \) where \( k \) is the wave number, see also Li and Kareem [31].

The spectral density of a stochastic process is the Fourier transform of its covariance function. The increment process \( X_t = B_{H,\lambda}(t+1) - B_{H,\lambda}(t) \) of a tempered fractional Brownian motion has spectral density

\[
h(k) = \frac{C|e^{-ik} - 1|^2}{(\lambda^2 + k^2)^{H+1/2}} \tag{32}
\]

for all real \( k \), where \( C > 0 \) is some constant [47, Remark 4.3]. Since \( e^{-ik} - 1 \sim -ik \) as \( k \to 0 \), this leads to the low frequency approximation

\[
h(k) \approx C \frac{k^2}{(\lambda^2 + k^2)^{H+1/2}},
\]

which shows that the stochastic process \( X_t \) has the Davenport spectrum with \( H = 5/6 \) and \( \lambda = V_{10}/1200 \). The process \( X_t \) is called a tempered fractional Gaussian noise.

Fig. 3 plots the spectral density of this tempered fractional Gaussian noise, along with the corresponding fractional Gaussian noise (the case \( \lambda = 0 \)). Here we take \( \lambda = 0.01 \) to represent an average wind speed of 12 m/s. The low frequency range corresponds to large eddy production. In the high frequency range, energy is dissipated via shear stress. In the intermediate (inertial) range, energy is transferred from smaller to larger eddies, and this is where the Kolmogorov model pertains. In that model, the spectral density is proportional to \( |k|^{1-2H} \) for moderate frequencies. For more details, see for example Pérez Beaupuits et al. [6].

In the inertial range, it can be seen from Fig. 3 that the spectrum of tempered fractional Gaussian noise is almost indistinguishable from that of (untempered) fractional Gaussian noise. However, there is a significant difference at low frequencies. The spectral density of fractional Gaussian noise diverges to infinity, which is not physical. However, the spectral density of tempered fractional Gaussian noise remains bounded, providing a more reasonable model for turbulence, consistent with the Davenport spectrum.

The Davenport model for wind turbulence is widely used to design windmill farms, offshore oil platforms, and large antennae [6,16,25,53], but to date the model provides only a spectrum for wind speed data. Tempered fractional Gaussian noise...
Fig. 3. Spectral density of tempered fractional Gaussian noise with $H = 5/6$ and $\lambda = 0.01$ (solid line) and of the corresponding fractional Gaussian noise with $H = 5/6$ (dashed line).

noise, the increments of a tempered fractional Brownian motion, provides a stochastic process model in the time domain, which can also be useful in applications. For example, it can be used to simulate realistic wind speed data. It may also be useful to apply tempered fractional Brownian motion with $H \approx 1/3$ as a model for turbulence in a more general setting. In the inertial range, it agrees well with the original Kolmogorov model (fractional Brownian motion), but it would seem to provide a more reasonable physical model at low frequencies.

The ARTFIMA process from Section 6 is the discrete time analogue of a tempered fractional Gaussian noise. Hence it could also provide a useful model for turbulence, when applied for example to a time series of turbulent velocities. From (30) we see that the ARTFIMA($p, \alpha, \lambda, q$) spectral density is proportional to $|1 - e^{-(\lambda + ik)}|^{-2\alpha}$ and so, for small values of the tempering parameter $\lambda \approx 0$, the spectral density is approximately $|k|^{1-2H}$ for small frequencies $k$, recalling that $\alpha = 1/2 - H$. As $k \to 0$, the spectral density remains bounded, because of the tempering.

8. Summary

Fractional calculus is a very useful analytical toolbox, with many diverse applications to all areas of science and engineering. This paper is promoting a new variation called tempered fractional calculus, as a more flexible alternative with considerable promise for practical applications. A fractional derivative (or integral) is a (distributional) convolution with a power law. A tempered fractional derivative multiplies that power law kernel by an exponential factor. Fractional diffusion equations govern random walks with a power law probability density for the particle jumps. Multiplying that power law by an exponential tempering factor leads to a tempered fractional diffusion equation. Point source solutions to those equations are tempered stable probability densities, with semi-heavy tails that transition from power law to Gaussian. The emerging theory of tempered fractional calculus provides a sound mathematical basis for applications. Tempered fractional Brownian motion, the tempered fractional derivative or integral of a Brownian motion, extends the popular fractional Brownian motion, and provides a flexible model for semi-long range dependence that transitions from long to short range correlations. The tempered fractional difference operator can provide the basis for effective numerical schemes to solve tempered fractional differential equations. It is also useful as a model for time series analysis, where ARTFIMA($p, \alpha, \lambda, q$) models incorporate semi-long range dependence in a natural way. Tempered fractional Brownian motion provides a new stochastic process model for turbulence, consistent with the Davenport spectrum that extends the Kolmogorov theory of turbulence beyond the inertial range, and the ARTFIMA($p, \alpha, \lambda, q$) model provides a useful discrete time analogue.

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