

Nonlinear stochastic differential equations and $1/f$ noise

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- 1 Introduction: $1/f$ noise
- 2 Stochastic differential equations giving $1/f$ noise
- 3 Some models resulting in proposed SDE
 - Point processes
 - Simple model of herding behavior
- 4 Summary

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What is $1/f$ noise?

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a type of noise whose power spectral density $S(f)$ behaves like

$$S(f) \sim 1/f^\beta, \quad \beta \text{ is close to } 1$$

- occasionally called “flicker noise”
- or “pink noise”

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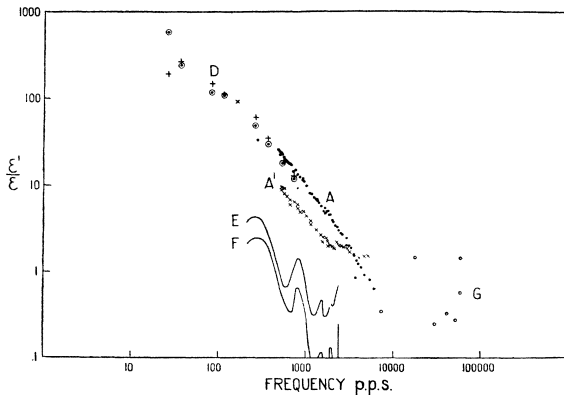


Fig. 6. Frequency variation for tube No. 2, coated filament; same data as in Fig. 4 plotted to a frequency scale; curves E and F give Hartmann's results for 2 m-a. and 20 m-a.; points G were obtained with less steady measuring circuit.

First observed (in 1925) by Johnson in vacuum tubes.

1/f noise

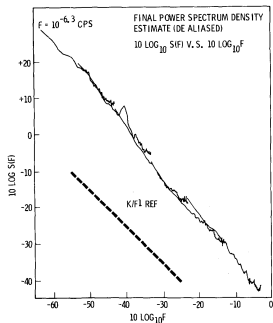


FIG. 8. Final power spectrum density estimate (dealiased).

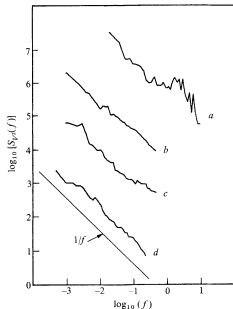
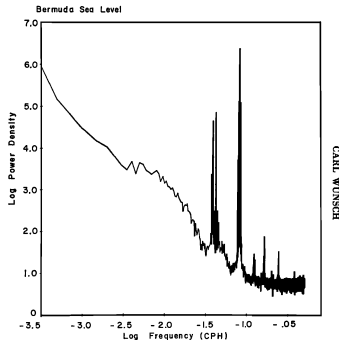


Fig. 2 Loudness fluctuation spectrum, $S_v(f)$ against f for: a, Scott Joplin Piano Rags; b, classical radio station; c, rock station; d, news and talk station.



Fluctuations of signals exhibiting $1/f$ behavior of the power spectral density at low frequencies have been observed in a **wide variety** of physical, geophysical, biological, financial, traffic, Internet, astrophysical and other systems.

Many mathematical models:

- Superposition of relaxation processes

$$S(f) = \int_{\gamma_1}^{\gamma_2} \frac{N}{\gamma^2 + \omega^2} d\gamma \approx \frac{\pi N}{2\omega}, \quad \gamma_1 \ll \omega \ll \gamma_2$$

- Dynamical systems at the edge of chaos

$$x_{n+1} = x_n + x_n^z \pmod{1}$$

- Alternating fractal renewal process

- Self-Organized Criticality

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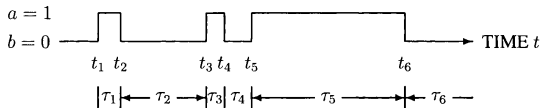
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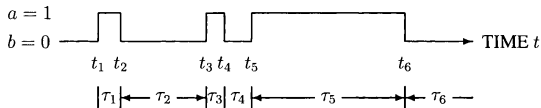
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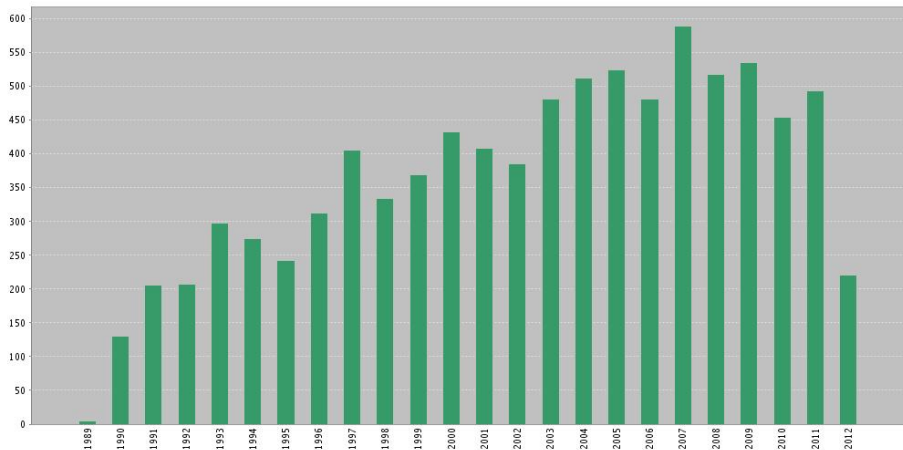
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A bibliography on $1/f$ noise is vast



Published items in each year. Topic: $1/f$ noise, $1/f$ fluctuations, flicker noise, pink noise (Web of Science)

$1/f$ noise

- $1/f$ noise is intermediate between white noise, $S(f) \sim 1/f^0$ and Brownian motion $S(f) \sim 1/f^2$
- In contrast to the Brownian motion generated by the linear stochastic equations, the signals and processes with $1/f$ spectrum **cannot** be understood and modeled in such a way.

Goal

to find a simple **nonlinear** stochastic differential equation (SDE) generating signals exhibiting $1/f$ noise

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Notes about $1/f$ noise

- Often $1/f$ noise is defined by a long-memory process, characterized by $S(f) \sim 1/f^\beta$ as $f \rightarrow 0$.
- A **pure** $1/f$ power spectrum is **physically impossible** because the total power would be infinity.
- We search for a model where the spectrum of signal has $1/f^\beta$ behavior only in some **intermediate** region of frequencies, $f_{\min} \ll f \ll f_{\max}$, whereas for small frequencies $f \ll f_{\min}$ the spectrum is bounded.

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Heuristic derivation of SDE

- If $S(f) \sim f^{-\beta}$ then power spectral density has a scaling property

$$S(af) = a^{-\beta} S(f)$$

- Wiener-Khintchine theorem

$$C(t) = \int_0^{+\infty} S(f) \cos(2\pi ft) df$$

- Autocorrelation function $C(t)$ has scaling property

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$$C(t) = \int dx \int dx' xx' P_0(x) P_x(x', t|x, 0)$$

- $P_0(x)$ is the steady state PDF
- $P_x(x', t|x, 0)$ is the transition probability
- The transition probability can be obtained from the solution of the **Fokker-Planck equation** with the initial condition $P_x(x', 0|x, 0) = \delta(x' - x)$.

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- Steady state PDF has power-law form

$$P_0(x) \sim x^{-\nu}$$

- Transition probability has a scaling property

$$P(ax', t|ax, 0) = a^{-1} P(x', a^{2(\eta-1)}t|x, 0)$$

- Then the autocorrelation function will have the required scaling with

$$\beta = 1 + \frac{\nu - 3}{2(\eta - 1)}$$

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- SDE should contain only powers of x
- The diffusion coefficient should be of the form $x^{2\eta}$
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Proposed SDE

$$dx = \sigma^2(\eta - \nu/2)x^{2\eta-1}dt + \sigma x^\eta dW_t$$

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Transformation property

Introducing

$$z = x^\alpha$$

we get the equation **of the same type**

$$dz = \sigma'^2(\eta' - \nu'/2)z^{2\eta'-1}dt + \sigma'z^{\eta'}dW_t$$

only with different parameters

$$\sigma' = \alpha\sigma, \quad \eta' = (\eta - 1)/\alpha + 1, \quad \nu' = (\nu - 1)/\alpha + 1$$

Restriction of diffusion

- Because of the divergence of the power-law distribution and the requirement of the stationarity of the process, the SDE should be analyzed together with the appropriate **restrictions** of the diffusion in some finite interval.
- When diffusion is restricted, **scaling properties are only approximate**, but $1/f$ spectrum remains in a wide interval of frequencies.

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Restriction of diffusion

Possible forms of restriction:

- Reflective boundary conditions at $x = x_{\min}$ and $x = x_{\max}$
- Exponential restriction of the diffusion

$$dx = \sigma^2 \left(\eta - \frac{\nu}{2} + \frac{m}{2} \left(\frac{x_{\min}}{x} \right)^m - \frac{m}{2} \left(\frac{x}{x_{\max}} \right)^m \right) x^{2\eta-1} dt + \sigma x^\eta dW_t$$

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- q -exponential steady-state PDF

$$dx = \sigma^2(\eta - \nu/2)(x + x_0)^{2\eta-1}dt + \sigma(x + x_0)^\eta dW_t$$

$$P_0(x) \sim \exp_{1+1/\nu}(-\nu x/x_0)$$

Reflective boundary condition at $x = 0$

- q -Gaussian steady-state PDF

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Connection with other equations

For some choices of parameters our SDE takes the form of well-known equations.

- $\eta = 0$ and $\sigma = 1$ corresponds to the **Bessel process**

$$dx = \frac{\delta - 1}{2} \frac{1}{x} dt + dW_t$$

of dimension $\delta = 1 - \nu$

- $\eta = 1/2$, $\sigma = 2$ corresponds to the **squared Bessel process**

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Connection with other equations

- SDE with exponential restriction with $\eta = 1/2$, $x_{\min} = 0$ and $m = 1$ gives **Cox-Ingersoll-Ross (CIR) process**

$$dx = k(\theta - x)dt + \sigma\sqrt{x}dW_t$$

where $k = \sigma^2/2x_{\max}$, $\theta = x_{\max}(1 - \nu)$

- When $\nu = 2\eta$, $x_{\max} = \infty$ and $m = 2\eta - 2$ then we get the **Constant Elasticity of Variance (CEV) process**

$$dx = \mu x dt + \sigma x^\eta dW_t$$

where $\mu = \sigma^2(\eta - 1)x_{\min}^{2(\eta-1)}$

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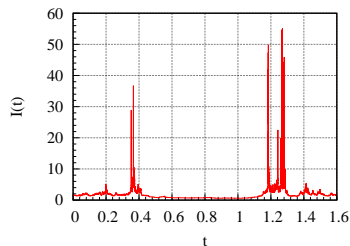
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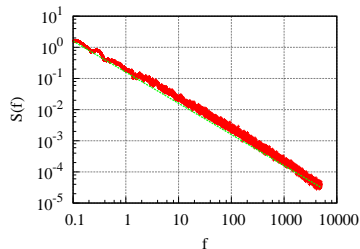
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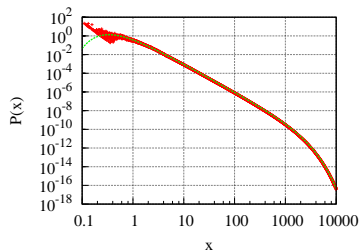
Numerical example



Typical signal



Power spectral density



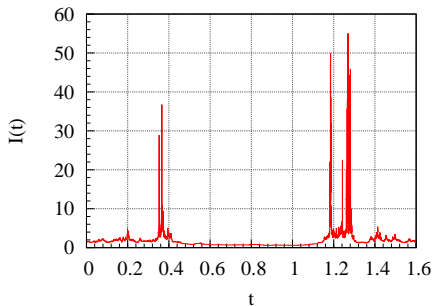
Distribution of x

$$dx = \left(1 + \frac{x_{\min}}{2x} - \frac{x}{2x_{\max}}\right) x^4 dt + x^{\frac{5}{2}} dW_t$$

$$\nu = 3, \eta = \frac{5}{2}, x_{\min} = 1, x_{\max} = 10^3.$$

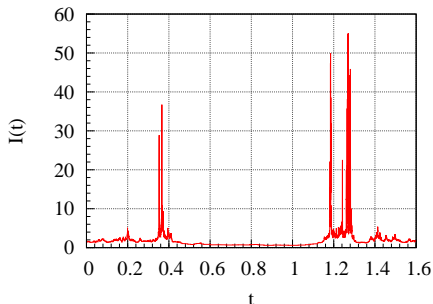
1/f spectrum.

Intermittent behavior of solutions



- Signals generated by proposed SDE exhibit **intermittent behavior**: there are bursts corresponding to large deviations, separated by laminar phases.
- Bursts are characterized by power-law distributions of burst size, burst duration, and interburst time.

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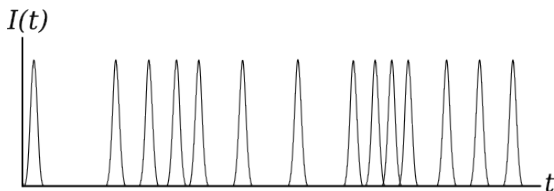


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 - Point processes
 - Simple model of herding behavior
- 4 Summary

Point processes

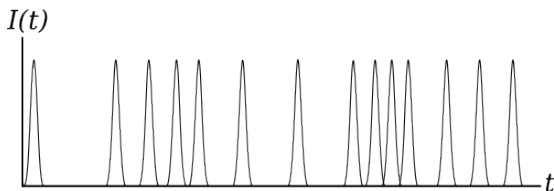


- The signal of the model consists of pulses or events

$$I(t) = a \sum_k \delta(t - t_k)$$

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How to obtain equation for inter-event time $\tau_k = t_k - t_{k-1}$:

- Transform the equation from the variable x to $\tau = 1/x$
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Example: equation

$$dx = \sigma^2 x^4 dt + \sigma x^{5/2} dW$$

leads to

$$\tau_{k+1} = \tau_k + \sigma \varepsilon_k$$

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- General case

$$\tau_{k+1} = \tau_k + \gamma \tau_k^{2\mu-1} + \sigma \tau_k^\mu \varepsilon_k$$

where $\mu = 5/2 - \eta$, $\gamma = \sigma^2(1 - \eta + \nu/2)$.

- Used for modeling of the internote interval sequences of the musical rhythms

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Herding model

Simple model describing heterogeneous interacting agents:

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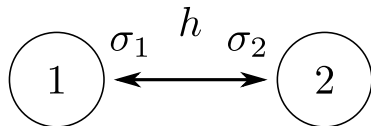
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- Transition probabilities per unit time:

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$$p(n \rightarrow n - 1) = n(\sigma_2 + h(N - n))$$



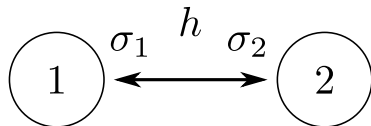
- n is the number of agents in state 1
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 - σ_1 and σ_2 are probabilities to change the state spontaneously
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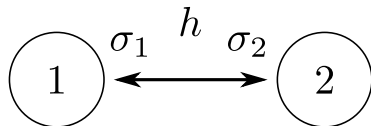
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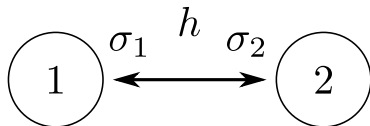
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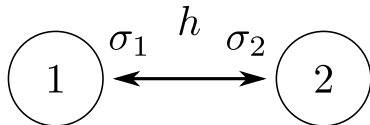
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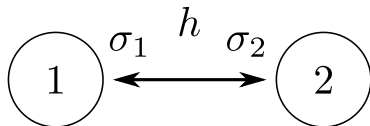
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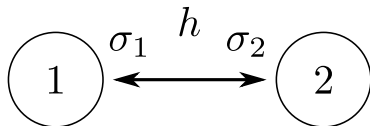
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- Ratio of the number of agents in the state 2 to the number of agents in the state 1:

$$y = \frac{N - n}{n}$$

- For large N we can represent the dynamics by SDE

$$dy = [(2h - \sigma_1)y + \sigma_2](1 + y)dt + \sqrt{2hy}(1 + y)dW$$

- When $y \gg 1$ we get our non-linear SDE with parameters $\eta = 3/2$, $\nu = 1 + \sigma_1/h$

If $\sigma_1 = 2h$, we obtain $1/f$ spectrum

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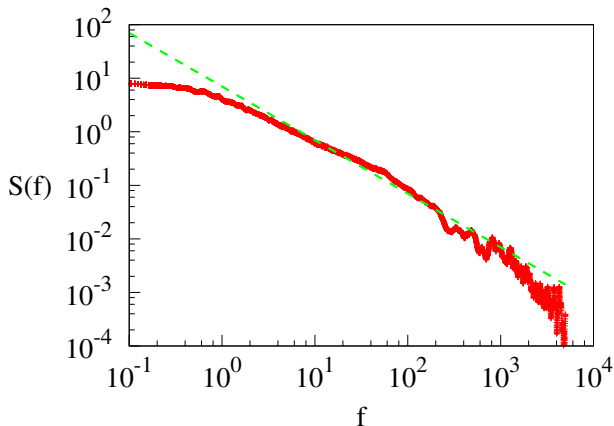
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Herding model



Power spectral density of the ratio of the numbers of agents.

$N = 10\,000$

Summary

- We obtain a class of nonlinear SDEs giving the power-law behavior of the power spectral density in any desirably wide range of frequencies
- and power-law steady state distribution of the signal intensity.
- In special cases we obtain other well-known SDEs.
- One of the reasons for the appearance of the $1/f$ spectrum are scaling properties of the SDE.
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