

# Modeling Gaussian and non-Gaussian $1/f$ noise by the linear stochastic differential equations

Bronislovas Kaulakys, Rytis Kazakevičius, Julius Ruseckas

Institute of Theoretical Physics and Astronomy, Vilnius University, A. Goštauto 12, LT-01108 Vilnius, Lithuania

**Abstract**—The ubiquitously observable  $1/f$  noise is mostly Gaussian but sometimes the non-Gaussianity is recognizable, as well. Here we consider stochastic models of  $1/f$  noise based on the linear stochastic differential equations with the very slowly varying coefficients (intensity of the white noise and relaxation rate) or consisting of a superposition of uncorrelated components with different distributions of these coefficients. We explore the conditions in which the modeled signal exhibiting  $1/f^\beta$  noise is Gaussian and when it is non-Gaussian, i.e., the power-law distributed.

## I. INTRODUCTION

Abundance of  $1/f$  distribution of the power spectral density have been found to be a key feature of a number of physical, natural, social, and biological phenomena [1], [2]. Mostly  $1/f$  noise is considered as Gaussian process [2], [3], but in some cases the signals exhibiting  $1/f$  fluctuations are non-Gaussian [4]–[9].

We have proposed stochastic models of  $1/f^\beta$  noise based on the nonlinear stochastic differential equations [10]–[14], starting from the point process model of  $1/f$  noise [15], [16]. The models generate signals with the power-law distributions of signal intensity and power-law spectral density. There exist other models of  $1/f$  noise, including the renewal point process with the power-law distribution of the interevent time [17] and random process represented by random pulses with randomly varying durations and amplitudes [18]–[21].

Nonetheless,  $1/f$  noise is often modeled as a sum of independent Lorentzian spectra, resulting from uncorrelated signals with wide-range distributions of the relaxation times  $\tau_{\text{rel}}$  [16], [22]. Distribution densities  $P_l(x_l)$  of the signal components  $x_l$  modeled by the linear stochastic differential equations

$$dx_l = -\gamma_l x_l dt + \sigma_l dW_t \quad (1)$$

are Gaussian,

$$P_l(x_l) = \frac{1}{\sigma_l} \sqrt{\frac{\gamma_l}{\pi}} \exp\left[-\frac{\gamma_l}{\sigma_l^2} x_l^2\right]. \quad (2)$$

Here  $\gamma_l = 1/\tau_l^{\text{rel}}$  is the linear relaxation rate,  $\sigma_l$  is the white noise intensity, and  $W_t$  is the standard Wiener process (Brownian motion). The signal generated by Eq. (1) has the correlation function

$$C_l(s) = \frac{\sigma_l^2}{2\gamma_l} e^{-\gamma_l s}, \quad s \geq 0 \quad (3)$$

and the power spectral density

$$S_l(f) = \frac{2\sigma_l^2}{\gamma_l^2 + \omega^2}, \quad \omega = 2\pi f. \quad (4)$$

The shapes of the probability density function  $P(x)$  and of the power spectral density  $S(f)$  of the signal represented as a sum of uncorrelated components  $x_l(t)$ ,

$$x(t) = \sum_l x_l(t), \quad (5)$$

depend on the distribution of  $\gamma_l$  and  $\sigma_l$  [16], [23]. For instance, the distribution of relaxation rates  $g(\gamma) \sim \gamma^{-1}$  together with the dependence  $\sigma(\gamma) \sim \gamma^{1/2}$  yields  $1/f$  noise of the Gaussian distributed signal (5) [16], while the uniform distribution of  $\gamma$ ,  $g(\gamma) = \text{const}$ , with  $\sigma = \text{const}$ , results in  $1/f$  noise with the power-law distribution of  $x$ ,  $P(x) \sim 1/x^3$  [23].

## II. MODELING $1/f^\beta$ NOISE

In this paper we consider and analyze distributions and power spectra of signals (5) generated by the linear stochastic differential equations (1) or by equation

$$dx = -\gamma(t)x dt + \sigma(t)dW_t \quad (6)$$

with the very slowly fluctuating relaxation rate  $\gamma(t)$  and intensity of the white noise  $\sigma(t)$ . This model is a generalization of the model based on the linear stochastic differential equation with the diffusion-like fluctuations of relaxation rate and constant intensity of the white noise [23],

$$dx = -\gamma(t)x dt + \sigma dW_t. \quad (7)$$

Many non-equilibrium systems exhibit spatial or temporal fluctuations of some parameter. Usually there are two time scales. One time scale corresponds to the relaxation dynamics of the system to a stationary state, while another time scale is related to the fluctuating evolution of parameters. A particular case is when the relaxation time needed for the system to reach stationarity is much smaller than the time scale at which the fluctuating parameter changes. In such a case, in the long-term the non-equilibrium system is described by a superposition of different local dynamics at different time intervals. This framework has been called superstatistics [24]–[28]. The superstatistical approach has been successfully applied for a variety of problems, like interactions between hadrons from cosmic rays [29], fluid turbulence [30]–[33], granular material [34], electronics [35], and economics [36]–[41]. Recently the superstatistical approach in combination with the stochastic model of  $1/f$  noise has been used for modeling Tsallis distributions with the long-range correlations [14] and for simulation of the financial observables [42].

Our model presented in this paper may be considered as a specific case of the superstatistical approach, when the observable signal  $x(t)$  in (5) is a superposition of the constituents

generated by subsystems (1) with different parameters or the signal produced by a system with fluctuating parameters (6). In the superstatistical approach the distribution  $P(x)$  of the signal  $x(t)$  is a superposition of the conditional distribution  $P(x|\gamma)$  and of the local distribution of the relaxation rate  $\gamma$  in the wide interval  $\gamma \in [\gamma_1, \gamma_2]$  with  $\gamma_1 \ll \gamma_2$ , i.e., the density of the relaxation rates,  $g(\gamma)$ ,

$$P(x) = \int_{\gamma_1}^{\gamma_2} P(x|\gamma)g(\gamma)d\gamma. \quad (8)$$

The power spectral density of signal  $x(t)$  can be calculated in a similar manner [23]

$$S(f) = \int_{\gamma_1}^{\gamma_2} S(f|\gamma)g(\gamma)d\gamma. \quad (9)$$

Here  $S(f|\gamma)$  is the spectral density of signal  $x(t)$  for the fixed relaxation rate value  $\gamma$ .

We go beyond the fluctuation-dissipation theorem and the equipartition of energy theorem and introduce the relationship between relaxation rates and the intensity of the white noise in the most simple power-law way,

$$\sigma(\gamma) = \sigma_0\gamma^\mu. \quad (10)$$

Here  $\mu$  is a parameter that depends on the system.

There are some cases where the fluctuation-dissipation theorem cannot be applied. The violation of the fluctuation-dissipation theorem has been found in the finite dimensional spin glasses [43] and in the systems out of equilibrium [44]. The theoretical study of motion of colloidal particles being confined in a harmonic well and dragged by a shear flow also shows violation of the fluctuation-dissipation theorem [45].

We analyze Eqs. (1) and (6) as Ito stochastic differential equations

$$dx = a(x)dt + b(x)dW_t. \quad (11)$$

For calculation of the steady state probability density function of the signal  $x$  we use the Fokker-Planck equation. The Fokker-Planck equation for the probability density function  $P(x)$  corresponding to the Ito equation (11) is [46]

$$\frac{\partial}{\partial t}P = -\frac{\partial}{\partial x}a(x)P + \frac{1}{2}\frac{\partial^2}{\partial x^2}b^2(x)P. \quad (12)$$

The steady state solution of Eq. (12) has the form

$$P(x|a, b) = \frac{C}{b^2(x)} \exp\left(\int_0^x \frac{2a(x_1)}{b^2(x_1)} dx_1\right). \quad (13)$$

For the fixed values of relaxation rate  $\gamma$  and white noise intensity  $\sigma(\gamma)$  the steady state distribution of the signal intensity is simply a Gaussian distribution,

$$P(x|\gamma, \sigma) = \frac{1}{\sigma(\gamma)} \sqrt{\frac{\gamma}{\pi}} \exp\left[-\frac{\gamma}{\sigma^2(\gamma)} x^2\right], \quad (14)$$

while the power spectral density of the signal  $x(t)$  intensity is simply the Lorentzian distribution,

$$S(f|\gamma) = \frac{2\sigma^2(\gamma)}{\gamma^2 + \omega^2}. \quad (15)$$

Recently we proposed a description of diffusion-like fluctuations of relaxation rate by the stochastic differential equation [23]

$$d\gamma = \sigma_\gamma \gamma^{-\frac{\eta}{2}} dW_t. \quad (16)$$

Here  $\sigma_\gamma$  determines the rapidity of change of the relaxation rate driven by the white noise with the factor  $\gamma^{-\frac{\eta}{2}}$ , which imposes the power-law steady state distribution of the relaxation rate  $\gamma$ ,  $g(\gamma) \sim \gamma^\eta$ . Using Eq. (13) we get the stationary distribution of the relaxation rates

$$g(\gamma) = \begin{cases} \frac{(1+\eta)}{\gamma_2^{1+\eta} - \gamma_1^{1+\eta}} \gamma^\eta, & \eta \neq -1, \\ \left[\ln\left(\frac{\gamma_2}{\gamma_1}\right)\gamma\right]^{-1}, & \eta = -1. \end{cases} \quad (17)$$

From Eqs. (9), (10), (15), and (17) we obtain the power spectral density

$$S(f) = \frac{C_\eta}{\omega^{1-(\eta+2\mu)}} \left\{ \left[\frac{\gamma_2}{\omega}\right]^{1+\eta+2\mu} \Phi\left(-\frac{\gamma_2^2}{\omega^2}, 1, \frac{1+\eta+2\mu}{2}\right) - \left[\frac{\gamma_1}{\omega}\right]^{1+\eta+2\mu} \Phi\left(-\frac{\gamma_1^2}{\omega^2}, 1, \frac{1+\eta+2\mu}{2}\right) \right\}. \quad (18)$$

Here  $\Phi(z, s, a)$  is the Lerch's phi transcendent and  $C_\eta$  is the normalization constant

$$C_\eta = \frac{\sigma_0^2(1+\eta)}{(\gamma_2^{\eta+1} - \gamma_1^{\eta+1})}. \quad (19)$$

In the frequency range  $\gamma_1 \ll f \ll \gamma_2$ , the power spectral density (18) is well approximated by the expression

$$S(f) = \frac{\sigma_0^2(1+\eta)(2\pi)^{\eta+2\mu}}{2(\gamma_2^{\eta+1} - \gamma_1^{\eta+1}) \cos\left(\frac{\pi(\eta+2\mu)}{2}\right)} \frac{1}{f^{1-(\eta+2\mu)}}, \quad (20)$$

$$|\eta + 2\mu| < 1.$$

Therefore, when the condition  $|\eta + 2\mu| < 1$  is satisfied, then  $1/f^\beta$  noise,

$$S(f) \sim 1/f^\beta, \quad \beta = 1 - (\eta + 2\mu), \quad (21)$$

may be observed and the exponent  $\beta$  varies between 0 and 2. For  $|\eta + 2\mu| > 1$  the  $1/f^\beta$  noise is not detectable.

From Eqs. (8), (10), (14), and (17) we obtain the steady state probability density function

$$P(x) = \begin{cases} C \frac{1}{x^\lambda} \left[ \Gamma\left(\frac{\lambda}{2}, \frac{\gamma^{1-2\mu} x^2}{\sigma_0^2}\right) \right]_{\gamma_2}^{\gamma_1}, & \mu \neq \frac{1}{2}, \\ \frac{1}{\sigma_0 \sqrt{\pi}} e^{-\frac{x^2}{\sigma_0^2}}, & \mu = \frac{1}{2}, \end{cases} \quad (22)$$

$$C = \frac{(1+\eta)}{\gamma_2^{\eta+1} - \gamma_1^{\eta+1}} \frac{\sigma_0^{\lambda-1}}{\sqrt{\pi}(1-2\mu)}. \quad (23)$$

Here  $C$  is the normalization constant and  $\lambda$  is the exponent of the power-law,

$$\lambda = 3 + \frac{2(\eta + 2\mu)}{1 - 2\mu}. \quad (24)$$

If inequality  $x_{\min} \ll x \ll x_{\max}$ , where  $x_{\min} = \sigma_0 \gamma_2^{\mu-1/2}$  and  $x_{\max} = \sigma_0 \gamma_1^{\mu-1/2}$ , is satisfied then for  $\mu \neq 1/2$  the distribution  $P(x)$  behaves like the power-law,

$$P(x) = \frac{(1+\eta)}{\sqrt{\pi}(\gamma_2^{\eta+1} - \gamma_1^{\eta+1})} \frac{\sigma_0^{\lambda-1} \Gamma(\frac{\lambda}{2})}{|1-2\mu|} \frac{1}{x^\lambda}. \quad (25)$$

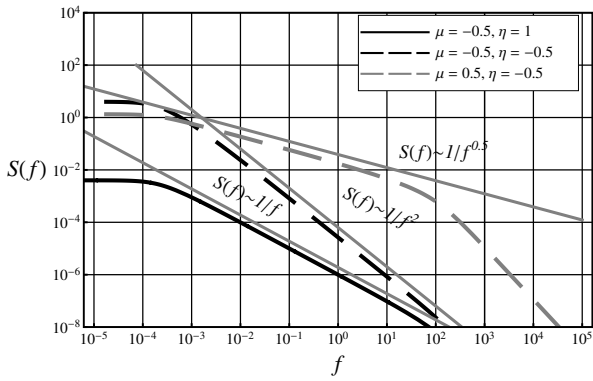


Fig. 1. Power spectral density  $S(f)$  calculated using Eq. (18) with different values of parameters  $\mu$  and  $\eta$  presented in the legend. Other parameters are:  $\gamma_1 = 0.001$ ,  $\gamma_2 = 1000$ , and  $\sigma_0 = 1$ .

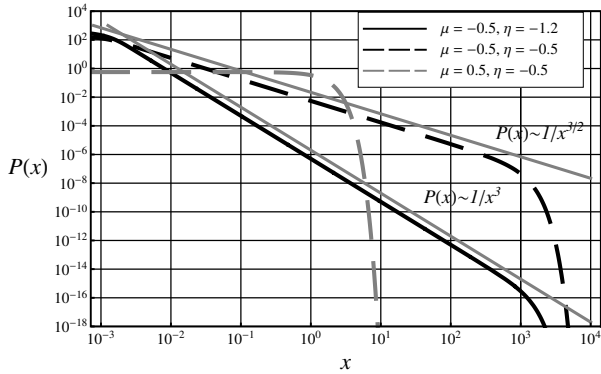


Fig. 2. Steady state probability density function  $P(x)$  calculated using Eq. (22) with different parameter values  $\mu$  and  $\eta$  presented in the legend. Other parameters are the same as in Fig. 1

Equation (25) approximates the probability density function (22) if conditions  $\lambda > 0$  and  $\mu \neq 0.5$  are satisfied.

The power spectral density and the probability density function of the signal  $x(t)$  intensity with different values of the parameters  $\eta$  and  $\mu$  are represented in Fig. 1 and Fig. 2. The black curves represent a case when  $\eta$  and  $\mu$  satisfy conditions  $|\eta + 2\mu| < 1$  and  $\lambda > 0$ . In this case we observe  $1/f^\beta$  noise with  $0 < \beta < 2$  and the power-law distribution of the signal,  $P(x) \sim 1/x^\lambda$ . The black dashed curves represent a case when  $\lambda > 0$ , but  $|\eta + 2\mu| > 1$ . In such a case we detect the Brownian noise with  $S(f) \sim 1/f^2$ . However, the probability density is non-Gaussian and we observe the power-law unless  $\mu = 1/2$ . Just in a special case when  $\mu = 1/2$  and  $|\eta + 1| < 1$  we have the Gaussian  $1/f^\beta$  noise (gray dashed curves).

### III. VALUES OF PARAMETERS $\mu$ AND $\eta$ FOR GENERATION OF $1/f^\beta$ NOISE WITH THE POWER-LAW DISTRIBUTION OF SIGNAL INTENSITY

Our models (1) and (6) generate probability density function of signal intensity in the range between  $x_{\min}$  and  $x_{\max}$  as power-law,  $P(x) \sim x^{-\lambda}$ , for different parameters except  $\mu = 0.5$ . From Fig. 1 and Fig. 2 (black dashed curve) it is evident that for signals with the power-law probability density function,  $1/f^\beta$  noise is not always observable. For some parameters the spectrum has  $S(f) \sim 1/f^2$  tails (Fig. 1 black

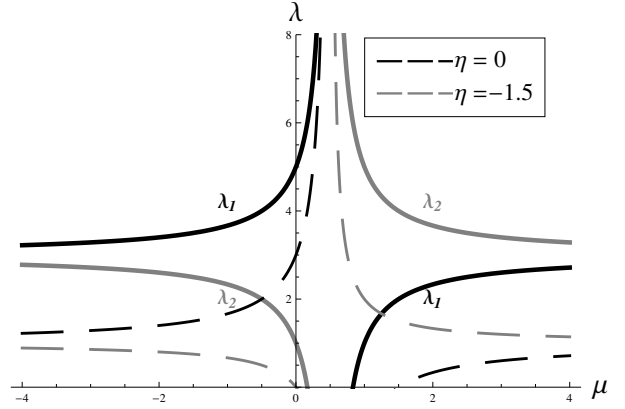


Fig. 3. The power-law exponent  $\lambda(\mu)$ , (24), dependence on the parameters  $\mu$  and  $\eta$ .  $\lambda_1(\mu)$  according to (27) (black curve) and  $\lambda_2(\mu)$  according to (28) (gray curve) restrict an area  $\lambda(\mu)$  where the condition  $|\eta + 2\mu| < 1$  is satisfied. Only in the parts of  $\lambda(\mu, \eta = \text{const})$  between dashed curves  $\lambda_1(\mu)$  and  $\lambda_2(\mu)$  the condition  $|\eta + 2\mu| < 1$  is satisfied and the power-law distribution is evident.

dashed curve). We now explore how to choose the values of the parameters  $\eta$  and  $\mu$  in order to generate signals with the non-Gaussian  $1/f^\beta$  noise and the possible values of the parameter  $\lambda$ . As it was shown above,  $1/f^\beta$  noise with the power-law distribution of the signal may be generated when the condition  $|\eta + 2\mu| < 1$  is satisfied, i.e., for  $\eta > -1 - 2\mu$  or  $\eta < 1 - 2\mu$ . Thus we have  $1/f^\beta$  noise with the power-law distribution if the parameter  $\eta$  belongs to the interval  $\eta \in (\eta_1(\mu), \eta_2(\mu))$ , where

$$\eta_1(\mu) = -1 - 2\mu, \quad (26)$$

$$\eta_2(\mu) = 1 - 2\mu.$$

From relations (24) and (26) we obtain that  $1/f^\beta$  noise with the power-law distribution of the signal is generated if the parameter  $\lambda$  belongs to the interval  $\lambda \in (\lambda_1, \lambda_2)$ , where

$$\lambda_1 = 3 - \frac{2}{1 - 2\mu}, \quad (27)$$

$$\lambda_2 = 3 + \frac{2}{1 - 2\mu}. \quad (28)$$

Functions  $\lambda_1(\mu)$  and  $\lambda_2(\mu)$  are plotted in Fig. 3. These functions restrict an area where the exponent  $\lambda(\mu)$  satisfies the condition  $|\eta + 2\mu| < 1$ . Using curves  $\lambda(\mu, \eta = \text{const})$  we can plot the area between  $\lambda_1(\mu)$  and  $\lambda_2(\mu)$  where the exponent  $\lambda$  can have values between 0 and  $\infty$  for the special choice of the parameters  $\eta$  and  $\mu$ . Equations (21) and (24) yield the relationship

$$\beta = 1 + (\mu - 1/2)(\lambda - 3), \quad (29)$$

similar to that obtained in the nonlinear models [12]–[14].

### IV. PURE $1/f$ NOISE

From relation (20) it is obvious that the pure  $1/f$  noise is generated when the condition  $\eta + 2\mu = 0$  is satisfied, i.e., when

$$\eta = -2\mu. \quad (30)$$

In the frequency range  $\gamma_1 \ll f \ll \gamma_2$  Eqs. (22) and (30) yield signal with pure  $1/f$  noise,

$$S(f) = \frac{\sigma_0^2(1+\eta)}{2(\gamma_2^{\eta+1} - \gamma_1^{\eta+1})} \frac{1}{f}, \quad \eta = -2\mu, \quad (31)$$

and the probability density function

$$P(x) = \begin{cases} \frac{\sigma_0^2}{\sqrt{\pi}(\gamma_2^{1+\eta} - \gamma_1^{1+\eta})} \frac{1}{x^3} \left[ \Gamma\left(\frac{3}{2}, \frac{\gamma^{1+\eta} x^2}{\sigma_0^2}\right) \right]_{\gamma_2}^{\gamma_1}, & \eta \neq -1, \\ \frac{1}{\sigma_0 \sqrt{\pi}} e^{-\frac{x^2}{\sigma_0^2}}, & \eta = -1. \end{cases} \quad (32)$$

In the interval between  $x_{\min} = \sigma_0 \gamma_2^{-(1+\eta)/2}$  and  $x_{\max} = \sigma_0 \gamma_1^{-(1+\eta)/2}$  the probability density function (32) can be approximated as

$$P(x) = \frac{\sigma_0^2 \operatorname{sgn}(1+\eta)}{\pi(\gamma_2^{1+\eta} - \gamma_1^{1+\eta})} \frac{1}{x^3}. \quad (33)$$

## V. CONCLUSION

We show that only in a special case, when  $\langle x^2 \rangle = \sigma^2(\gamma)/(2\gamma) = \text{const}$ , i.e., when all fluctuators get equal average energy, we can obtain the Gaussian  $1/f^\beta$  noise. In all other cases  $1/f^\beta$  noise can be generated by the power-law distributed signal,  $P(x) \sim 1/x^\lambda$ , with  $\lambda = 3$  corresponding to the pure  $1/f$  noise, as in the nonlinear case [12]–[14]. Beyond the equipartition theorem, the non-Gaussian  $1/f^\beta$  noise may be observed.

The proposed model of  $1/f^\beta$  noise extends our understanding of conditions for appearance of the phenomena in the complex systems with distinguishing long-range correlations and power-law distributions.

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