S1 On the $\Gamma_{n,\lambda}$ distributions from Gaussians with $\sigma \neq 1$

We want to fit the $\sigma^2 = \frac{1}{\beta}$ distributions as a convolution of exponential distributions. Let's first consider which is the general expression of a $\Gamma_{n,\lambda}$ coming from gaussian distributions with $\sigma \neq 1$ in general.

Let x_i be independent gaussian distributed random variables with zero mean ($\mu_i = 0$) and same variance ($\sigma_i = \sigma$):

$$f(x_i) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x_i^2}{2\sigma^2}}$$
(S1)

Let's define:

$$Q = \sum_{i=1}^{2n} x_i^2 \tag{S2}$$

So, calling V the elemental shell volume at Q(x), which is proportional to the (2n-1)-dimensional surface in 2n-space for which $Q = \sum_{i=1}^{2n} x_i^2$,

$$P(Q)dQ = \int_{V} \frac{e^{-\frac{1}{2\sigma^{2}}\left(x_{1}^{2}+x_{2}^{2}+...+x_{2n}^{2}\right)}}{(2\pi)^{2n/2}\sigma^{2n}} dx_{1}dx_{2}\cdots dx_{2n}$$

$$= \frac{e^{-\frac{Q}{2\sigma^{2}}}}{(2\pi)^{n}\sigma^{2n}} \int_{V} dx_{1}dx_{2}\cdots dx_{2n}$$

$$= \frac{e^{-\frac{Q}{2\sigma^{2}}}}{(2\pi)^{n}\sigma^{2n}} \cdot \frac{2Q^{\frac{2n-1}{2}}\pi^{n}}{\Gamma(n)} \cdot \frac{dQ}{2Q^{1/2}}$$

$$= \frac{Q^{n-1}e^{-\frac{Q}{2\sigma^{2}}}}{2^{n}\Gamma(n)\sigma^{2n}} \cdot dQ$$
(S3)

The resulting normalized $\Gamma_{n,\lambda}$ distribution (where $\lambda = 1/2\sigma^2$) with 2n degrees of freedom (the number of the added gaussian variables) is:

$$\Gamma_{n,\lambda}(Q) = \frac{Q^{n-1}e^{-\frac{Q}{2\sigma^2}}}{(2\sigma^2)^n\Gamma(n)} = \frac{\lambda^n Q^{n-1}e^{-\lambda Q}}{\Gamma(n)}$$
(S4)

Imponing 2n = 2 we obtain the exponential distribution:

$$\Gamma_{1,\lambda}(Q) = \frac{1}{2\sigma^2} \cdot e^{-\frac{Q}{2\sigma^2}} = \lambda e^{-\lambda Q}$$
(S5)

The mean value of a gamma distributed variable is:

$$\mu_{\Gamma,n} = \int_0^\infty Q\Gamma_{n,\lambda}(Q)dQ = \frac{n}{\lambda}$$
(S6)

The variance of a gamma distributed variable is:

$$\sigma_{\Gamma,n}^2 = \int_0^\infty Q^2 \Gamma_{n,\lambda}(Q) dQ - \mu_{\Gamma,n}^2 = \frac{n}{\lambda^2}$$
(S7)

Imponing n = 1 (the case of the exponential distribution) we obtain:

$$\sigma_{\exp}^2 := \sigma_{\Gamma,1}^2 = \frac{1}{\lambda^2} \tag{S8}$$

S2 On the convolution of $\Gamma_{1,\lambda}$ distributions

Let X and Y be two independent random variables distributed as $\Gamma_{1,\lambda}$ and $\Gamma_{1,k}$ respectively, see Equation (S5), where $\lambda = \frac{1}{2\sigma_X^2} > 0$ and $k = \frac{1}{2\sigma_Y^2} > 0$:

$$f_X(x) = \lambda e^{-\lambda x} \Theta_{(0,\infty)}(x)$$

$$f_Y(y) = k e^{-ky} \Theta_{(0,\infty)}(y)$$
(S9)

where

$$\Theta_{(a,b)}(t) = \begin{cases} 1 & \text{if } a \le t \le b \\ 0 & \text{otherwise} \end{cases}$$
(S10)

The two random variables X and Y are independent, so their joint probability distribution is:

$$f_{XY}(x,y) = f_X(x) \cdot f_Y(y) \tag{S11}$$

If we define a new random variable Z = X + Y, we will obtain:

$$f_Z(x,z) = f_X(x) \cdot f_Y(z-x)$$

= $\lambda k e^{-\lambda x} e^{-k(z-x)} \Theta_{(0,\infty)}(x) \Theta_{(0,\infty)}(z-x)$
= $\lambda k e^{-kz} e^{-(\lambda-k)x} \Theta_{(0,z)}(x)$ (S12)

So, we obtain the convolution:

$$f_Z(z) = \int_0^\infty f_Z(x, z) dx$$

= $\lambda k e^{-kz} \int_0^z e^{-(\lambda - k)x} dx$
= $\frac{\lambda k}{\lambda - k} (e^{-kz} - e^{-\lambda z})$ (S13)

The normalization can be easily checked.

S2.1 The case where $\lambda = k$

In the case where $\lambda = k$, it means that X and Y are identically distributed, so Z is the sum of n = 2 exponential processes (positive variables with maximum entropy distribution). We can interpret Z as the sum of 2n = 4 indipendent gaussian random variables with $\sigma_X^2 = \frac{1}{2\lambda}$:

$$Z \sim \Gamma_{2,\lambda}(z) = \lambda^2 z e^{-\lambda z} \tag{S14}$$

In this case the variance results:

$$\sigma_{\Gamma,2}^2 = \frac{2}{\lambda^2} \tag{S15}$$

In the following and in the paper, when we omit the pedix n = 2, we refer to the case n = 2:

$$\sigma_{\Gamma}^2 := \sigma_{\Gamma,2}^2 \tag{S16}$$

S3 The general case: the superstatistical combination of a gaussian distribution and a $\Gamma_{n,\lambda}$ distribution

The PDF of the total signal x is locally (in time) gaussian $N_{(0,z)}(x)$ with zero mean and the variance z varying (on longer time scales) following a $\Gamma_{n,\lambda}(z)$ distribution. The PDF p(x) of the total signal can be obtained in the following way (look at integral 16 page 369 of [1]):

$$p(x) = \int_{0}^{\infty} \Gamma_{n,\lambda}(z) \cdot N_{(0,z)}(x) dz$$

$$= \int_{0}^{\infty} \frac{\lambda^{n}}{\Gamma(n)} z^{n-1} e^{-\lambda z} \cdot \frac{1}{\sqrt{2\pi}\sqrt{z}} e^{-x^{2}/2z} dz$$

$$= \frac{\lambda^{n}}{\Gamma(n)\sqrt{2\pi}} \int_{0}^{\infty} z^{(n-1)-\frac{1}{2}} \cdot e^{-\lambda z - \frac{x^{2}/2}{z}} dz$$

$$= \frac{\lambda^{n}}{\Gamma(n)\sqrt{2\pi}} (-1)^{n-1} \sqrt{\pi} \frac{\partial^{n-1}}{\partial\lambda^{n-1}} \left(\frac{e^{-\sqrt{2\lambda x^{2}}}}{\sqrt{\lambda}} \right)$$

$$= \frac{(-1)^{n-1}\lambda^{n}}{\Gamma(n)\sqrt{2}} \cdot \frac{\partial^{n-1}}{\partial\lambda^{n-1}} \left(\frac{e^{-\sqrt{2\lambda} \cdot |x|}}{\sqrt{\lambda}} \right)$$

(S17)

with zero mean and variance s^2 :

$$s^{2} := var(x) = E[x^{2}]$$

$$= 2 \int_{0}^{\infty} \frac{(-1)^{n-1}\lambda^{n}}{\Gamma(n)\sqrt{2}} \cdot x^{2} \cdot \frac{\partial^{n-1}}{\partial\lambda^{n-1}} \left(\frac{e^{-\sqrt{2\lambda}\cdot x}}{\sqrt{\lambda}}\right) dx$$

$$= \frac{(-1)^{n-1}\lambda^{n}\sqrt{2}}{\Gamma(n)} \cdot \frac{d^{n-1}}{d\lambda^{n-1}} \left(\frac{1}{\sqrt{\lambda}}\int_{0}^{\infty} x^{2}e^{-\sqrt{2\lambda}\cdot x} dx\right)$$

$$= \frac{(-1)^{n-1}\lambda^{n}\sqrt{2}}{\Gamma(n)} \cdot \frac{d^{n-1}}{d\lambda^{n-1}} \left(\frac{1}{\sqrt{\lambda}} \cdot \frac{1}{2\lambda} \cdot \frac{1}{\sqrt{2\lambda}}\int_{0}^{\infty} y^{2}e^{-y} dy\right)$$

$$= \frac{(-1)^{n-1}\lambda^{n}}{\Gamma(n)} \cdot \frac{d^{n-1}}{d\lambda^{n-1}} \left(\frac{1}{\lambda^{2}}\right)$$

$$= \frac{(-1)^{n-1}\lambda^{n}}{\Gamma(n)} \cdot \frac{(-1)^{n-1}n!}{\lambda^{n+1}}$$

$$= \frac{n}{\lambda}$$
(S18)

The normalization of p(x) can be easily checked. We note that:

$$s^{2} = \frac{n}{\lambda} = \sqrt{n} \cdot \sigma_{\Gamma,n} = n \cdot \sigma_{\exp}$$
(S19)

S4 Our case

In our case:

$$\sigma_{\star}^2 \sim f(\sigma_{\star}^2) = \Gamma_{2,\lambda_{\star}}(\sigma_{\star}^2) = \lambda_{\star}^2 \sigma_{\star}^2 e^{-\lambda_{\star} \sigma_{\star}^2}$$
(S20)

Since our focus is on the variances (positive values), we can interpret n = 2 as the effective degree of freedom.

The velocity increment PDF is (see Eq. (S17) with n = 2):

$$p(\delta u) = \int_{0}^{\infty} f(\sigma_{\delta u}^{2}) p(\delta u | \sigma_{\delta u}^{2}) d(\sigma_{\delta u}^{2})$$

$$= \int_{0}^{\infty} \lambda_{\delta u}^{2} \sigma_{\delta u}^{2} e^{-\lambda_{\delta u} \sigma_{\delta u}^{2}} \cdot \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{\sigma_{\delta u}^{2}}} e^{-\delta u^{2}/2\sigma_{\delta u}^{2}} \cdot d(\sigma_{\delta u}^{2})$$

$$= -\frac{\lambda_{\delta u}^{2}}{\sqrt{2}} \cdot \frac{\partial}{\partial \lambda_{\delta u}} \left(\frac{e^{-\sqrt{2\lambda_{\delta u}} \cdot |\delta u|}}{\sqrt{\lambda_{\delta u}}} \right)$$

$$= \frac{\sqrt{2\lambda_{\delta u}} e^{-\sqrt{2\lambda_{\delta u}} |\delta u|} (\sqrt{2\lambda_{\delta u}} |\delta u| + 1)}{4}$$
(S21)

and analogously for δv . The normalization can be easily checked. The PDF is symmetric. The analytical velocity increment variance s_{\star}^2 is (see Eq. (S18) with n = 2):

$$s_{\delta u}^2 = \int_{-\infty}^{+\infty} \delta u^2 p(\delta u) d(\delta u) = \frac{2}{\lambda_{\delta u}}$$
(S22)

and analogously for δv . In the case n = 2, Eq. (S19) reduces to:

References

[1] Gradshteyn, Izrail Solomonovich, and Iosif Moiseevich Ryzhik. Table of integrals, series, and products. Academic press, 2014.