

# The $\alpha$ SGN( $m$ ) MATLAB toolbox

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Ahmed Mahmood (July 2018)

## Brief Intro.

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The aim of this toolbox is to incorporate emerging techniques related to  $\alpha$ -stable processes within Matlab's functionality. Our topic of interest is the  $\alpha$ SGN( $m$ ) model. As of now, literature on the topic can be found primarily at <https://arl.nus.edu.sg/twiki6/bin/view/ARL/Publications> and consists of (1)–(6) amongst others.

This document offers a quick overview of the toolbox. For more details, revert to the actual scripts. Before listing down the functions within this toolbox, we introduce a few concepts to aid the discussion:

The heavy-tailed  $\alpha$ SGN( $m$ ) process is derived from an  $(m + 1)$ -dimensional  $\alpha$ -sub-Gaussian ( $\alpha$ SG) distribution, which in turn is parameterized by the characteristic exponent  $\alpha \in (0, 2)$  and the covariance matrix  $\mathbf{R}$ . The  $\alpha$ SG distribution is elliptic and can be denoted by  $\alpha\text{SG}(\alpha, \mathbf{R})$  or equivalently by  $\alpha\text{SG}(\alpha, \delta, \mathbf{Cov})$ , where  $\mathbf{Cov}$  is the normalized covariance matrix and  $\delta \in (0, \infty)$  is the scale, i.e.,  $\mathbf{R} = \delta^2 \mathbf{Cov}$ . The  $\alpha$ SGN( $m$ ) process essentially constrains any of its  $(m + 1)$  adjacent samples to follow the aforementioned  $\alpha$ SG distribution. This ensures  $\mathbf{R}$  (and thus  $\mathbf{Cov}$ ) is a symmetric Toeplitz matrix. We note that each sample of an  $\alpha$ SGN( $m$ ) process is a symmetric  $\alpha$ -stable ( $S\alpha S$ ) random variable. The latter's distribution is completely characterized by the tuple  $(\alpha, \delta)$  and can be expressed as  $\mathcal{S}(\alpha, \delta)$ .

For more information about the employed parameterization, revert to (3). For a great introduction to  $\alpha$ SG distributions, do go through Nolan's discussion on the topic at <http://fs2.american.edu/jpnolan/www/stable/EllipticalStable.pdf>.

## Functions

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Add all directories to Matlab's path before use.

### Random variates

- `X = asgn(alpha, R, N, _')`: Generates  $N$  samples of  $\alpha$ SGN( $m$ ) with underlying distribution  $\alpha\text{SG}(\alpha, \mathbf{R})$ . The function accepts optional inputs as well (highlighted by `_`).
- `x = stabrnd(alpha, beta, delta, mu, N, M)`: McCulloch's original script that returns independent outcomes of the stable distribution  $\mathcal{S}(\alpha, \beta, \delta, \mu)$ , where `beta` is the skew parameter and `mu` is the location. Note that  $\mathcal{S}(\alpha, 0, \delta, 0)$  is statistically equivalent to  $\mathcal{S}(\alpha, \delta)$ . The outcomes are returned as the  $N \times M$  matrix `x`.

### Fitting

- `[alpha, mu, delta] = sstabfit(x)`: Mandar Chitre's script that fits an  $S\alpha S$  distribution to the data vector `x`.

- `[alpha, delta, Cov] = asgnfit(X, m, _)`: Estimates  $\alpha\text{SGN}(m)$  parameters from the data vector  $\mathbf{X}$  for a given  $m$ . Also, `_` signifies optional inputs.
- `[pxx, pasg, f] = asgnsd(X, fs)`: Determines `pxx`, the normalized non-parameterized spectral density, for the data vector  $\mathbf{X}$  sampled at `fs` kHz. The associated frequency vector `f` (in kHz) is also returned. Moreover, `pasg` is the closed-form *parametric* spectral density of  $\mathbf{X}$  evaluated under the assumption that  $\mathbf{X}$  holds consecutive samples of  $\alpha\text{SGN}(m)$ . Comparing `pxx` to `pasg` allows discerning a suitable  $m$  to characterize  $\mathbf{X}$  within the  $\alpha\text{SGN}(m)$  framework.

## Computing PDFs

- `logf_XN = asgnpdf(X, alpha, R)`: Samples the joint-pdf and returns its logarithm for each column (outcome) of  $\mathbf{X}$ , under the assumption that the columns hold consecutive samples of  $\alpha\text{SGN}(m)$  with underlying distribution  $\alpha\text{SG}(\alpha, R)$ .
- `f_X = saspdf(X, alpha, delta)`: Samples and returns the pdf associated with  $\mathcal{S}(\alpha, \delta)$  at each element (outcome) in the matrix  $\mathbf{X}$ . Note that `f_X` is the same size of  $\mathbf{X}$ .

## Storing and retrieving $\alpha\text{SGN}(m)$ data

As  $\alpha\text{SGN}(m)$  is a GARCH process, samples have to be sequentially computed. Consequently, `asgn()` can become a potential bottleneck for computation time when running intensive performance tests/simulations. To circumvent this, realizations may be pre-computed and stored offline, only to be retrieved for later use. The following functions are helpful in this regard:

- `asgn_write(alpha, Cov, FileSize, NumFiles, fs)`: Computes and stores a realization of  $\alpha\text{SGN}(m)$  with underlying distribution  $\alpha\text{SG}(\alpha, 1, \text{Cov}) = \alpha\text{SG}(\alpha, \text{Cov})$ . The samples are stored as `NumFiles` files, each of which is sized `FileSize` MBs. Also, `fs` is the associated sampling frequency. The files are stored in a sub-directory of the function's root folder. As an example, if `alpha = 1.57` and  $m = 4$  (implying `Cov` is a  $5 \times 5$  matrix), the files are saved in `"a1_57__m_4\"` and are labeled as `"asgn_1.bin"`, `"asgn_2.bin"` and so on.
- `[x, _] = asgn_read(fpath, samps, _)`: Reads `samps` samples from the files written by `asgn_write()`. The absolute path directory of these files is passed as the input string `fpath`.

## Miscellaneous

- `vr_validate`: refer to the script for details.

## References

1. A. Mahmood and M. Chitre, *Temporal Analysis of Stationary Markov  $\alpha$ -sub-Gaussian Noise*, in OCEANS 2016 MTS/IEEE, (Monterey, CA, USA), September 2016.
2. A. Mahmood, M. Chitre, and V. Hari, *Locally optimal inspired detection in snapping shrimp noise*, IEEE Journal of Oceanic Engineering, vol. 42, pp. 1049--1062, October 2017.

3. A. Mahmood and M. Chitre, *Generating Random Variates for Stable Sub-Gaussian Processes with Memory*, Signal Processing, vol. 131, pp. 271--279, February 2017.
4. A. Mahmood and M. Chitre, *Optimal and Near-Optimal Detection in Bursty Impulsive Noise*, IEEE Journal of Oceanic Engineering, vol. 42, pp. 639--653, October 2016.
5. A. Mahmood and M. Chitre, *Uncoded Acoustic Communication in Shallow Waters with Bursty Impulsive Noise*, in Underwater Communications Networking (Ucomms 2016), (Lerici, Italy), September 2016. (Invited).
6. A. Mahmood, V. Hari, and M. Chitre, *Model-Based Signal Detection in Snapping Shrimp Noise*, in Underwater Communications Networking (Ucomms 2016), (Lerici, Italy), September 2016. (Invited).