CS7GV2: Mathematics of Light and Sound, M.Sc. in Computer Science.

Lecture #6: Random Phasor Sums

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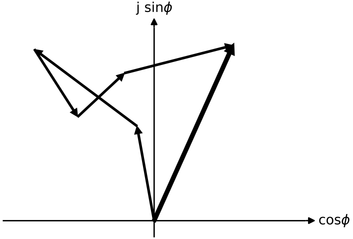
Random walks

Multiple wave phasors can be summed like vectors to find the *resultant* wave phasor at a point in space and time.

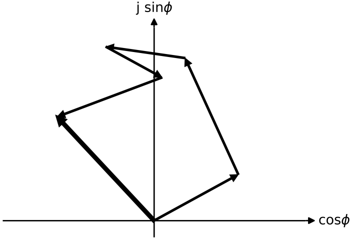
When wave amplitudes are independent and wave phases are independent* their summation is called a "random walk."

Random walks



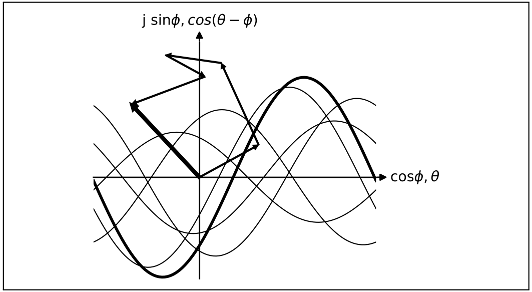
Multiple phasors and their resultant sum.

Random walks



Same amplitudes, different phases, smaller resultant.

Random walks



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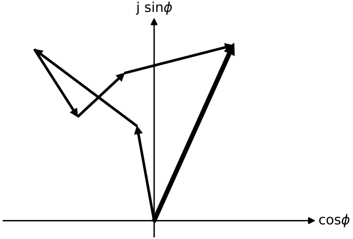

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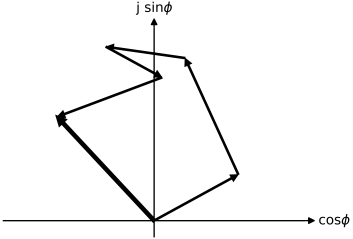

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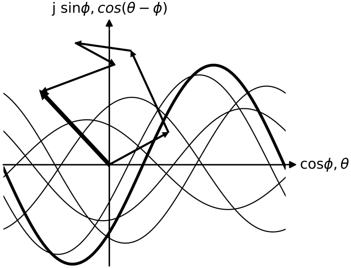

Independence and randomness

Independence means that one event or value of a random quantity X (e.g. a wave's amplitude) has no effect on another, Y (e.g. its phase,)

$$\mathbf{P}(X|Y) = \mathbf{P}(X \cap Y)/\mathbf{P}(Y)$$
$$\mathbf{P}(X \cap Y) = \mathbf{P}(X|Y)\mathbf{P}(Y)$$
$$\mathbf{P}(X \cap Y) = \mathbf{P}(X)\mathbf{P}(Y) \text{ i.f.f.}$$
$$\mathbf{P}(X) = \mathbf{P}(X|Y) \text{ and } \mathbf{P}(Y) = \mathbf{P}(Y|X).$$

Independence and randomness

A random quantity is one whose value depends on the outcome of a random phenomenon.

Its occurance may be known* to follow a particular probability density function f_X, or probability mass function p_X, with discriptive parameters μ, σ, etc.

Example PDFs are *Uniform, Normal, Exponential, Poisson, Rayleigh.*

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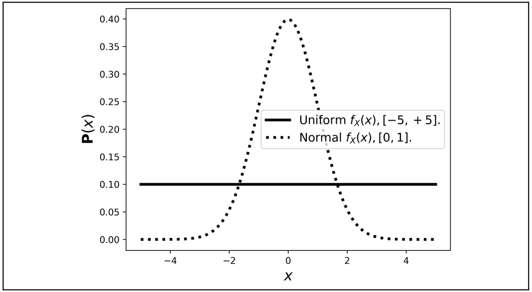

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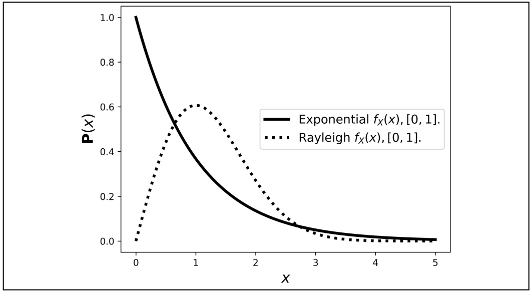

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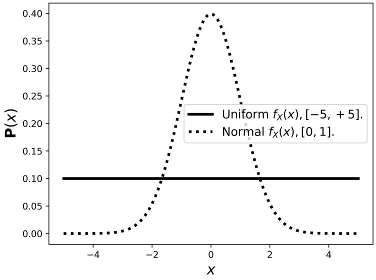
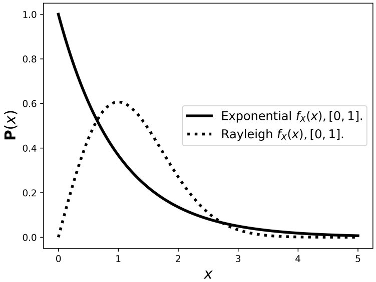
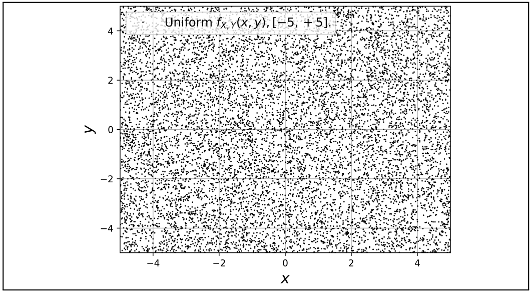
Example PDFs are *Uniform*, *Normal*, *Exponential*, *Poisson*, *Rayleigh*.





10,000 values (x, y) chosen randomly



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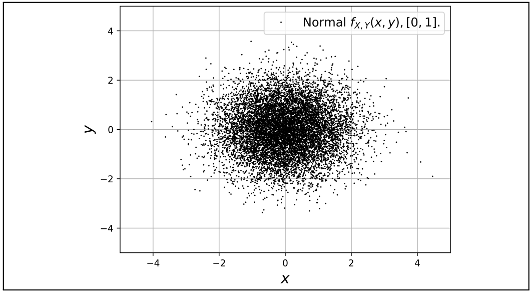

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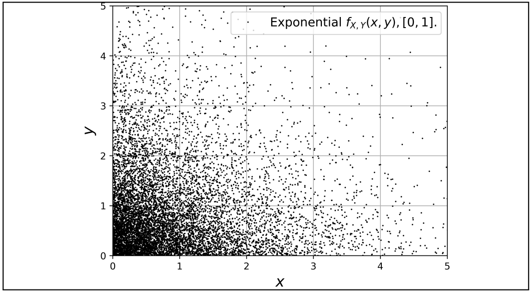

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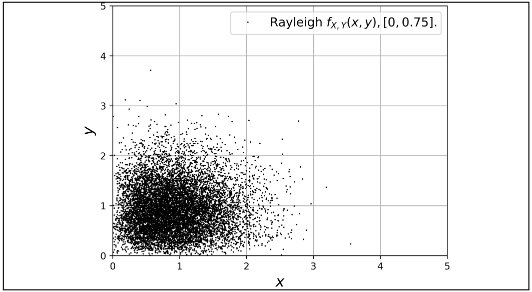

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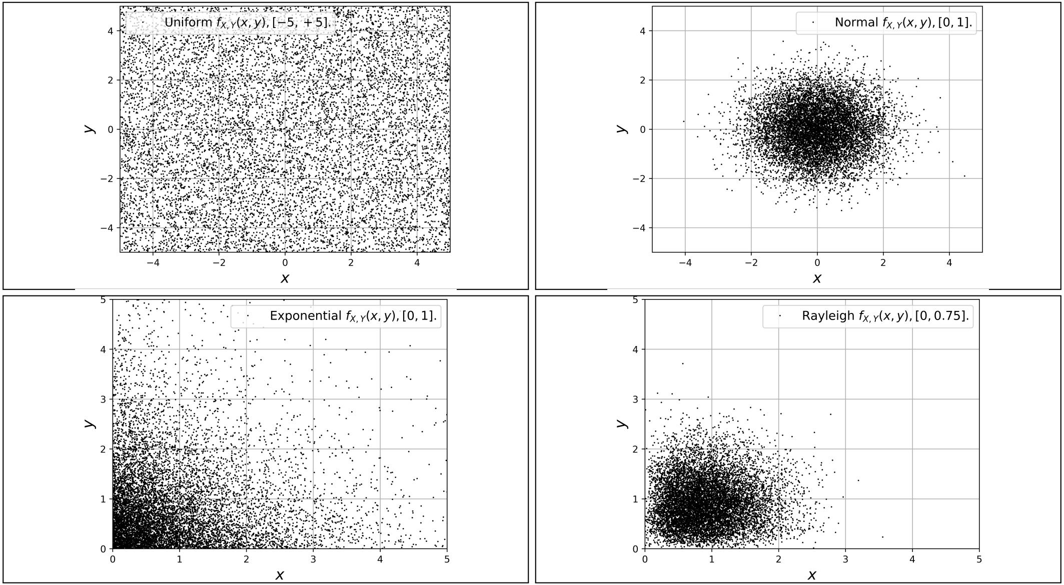

Descriptive statistics

Expected value or *mean* of a continuous random quantity X with probability density function f_X,

$$\mathbf{E}[X] = \int_{-\infty}^{+\infty} x \, f_X(x) \, \mathrm{d}x.$$

And for a discrete, finite, random quantity X with probability mass function p_X,

$$\mathbf{E}[X] = \sum_{i=1}^{N} x_i \, p_X(x_i).$$

Descriptive statistics

This is the *arithmetic mean* when probability mass function p_X is uniformly ${}^1/_N$.

$$\begin{aligned}\mathbf{E}[X] &= \textstyle\sum_{i=1}^{N} x_i \, {}^1/_N \\ &= {}^1/_N \textstyle\sum_{i=1}^{N} x_i \\ &= (x_1 + x_2 + \ldots x_N)/N\end{aligned}$$

Descriptive statistics

Linearity of expectation,

$$\mathbf{E}[X + Y] = \mathbf{E}[X] + \mathbf{E}[Y].$$

If $Y = aX + b$ for $a, b \in \mathbb{R}$,

$$\mathbf{E}[Y] = a\mathbf{E}[X] + b.$$

If X, Y independent,

$$\mathbf{E}[XY] = \mathbf{E}[X]\mathbf{E}[Y].$$

Descriptive statistics

Variance is mean distance squared to the mean (when uniform,)

$$\begin{aligned}\sigma_X^2 &= \mathbf{E}[(X - \mathbf{E}[X])^2] \\ &= \mathbf{E}[X^2] - \mathbf{E}[X]^2 \\ &= \mathbf{E}[X^2] \text{ when } \mathbf{E}[X] = 0.\end{aligned}$$

Standard deviation $\sigma_X = \sqrt{\sigma_X^2}$.

[cf. SCFT STD vs MAD.]

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Random phasor sum

Defined as a weighted sum of random phasors:

$$\frac{1}{\sqrt{N}} \sum_{n=1}^{N} a_n \mathrm{e}^{\mathrm{j}\,\phi_n} = \frac{1}{\sqrt{N}} \sum_{n=1}^{N} \boldsymbol{a}_n = A\mathrm{e}^{\mathrm{j}\,\theta}$$

$$= \boldsymbol{A} \quad \text{(the "resultant.")}$$

Random phasor sum

$$\begin{aligned}
\mathbf{E}[\mathrm{Re}\{\boldsymbol{A}\}] &= \mathbf{E}[{}^1\!/\!\sqrt{N}\sum_{n=1}^{N} a_n \cos\phi_n] \\
&= {}^1\!/\!\sqrt{N}\sum \mathbf{E}[a_n \cos\phi_n] \\
&= {}^1\!/\!\sqrt{N}\sum \mathbf{E}[a_n]\mathbf{E}[\cos\phi_n] \\
&= 0.
\end{aligned}$$

Similarly, $\mathbf{E}[\mathrm{Im}\{\boldsymbol{A}\}] = 0$.

Random phasor sum

$$
\begin{aligned}
\sigma^2_{\mathrm{Re}\{\boldsymbol{A}\}} &= \mathbf{E}[\mathrm{Re}\{\boldsymbol{A}\}^2]. \\
\mathrm{Re}\{\boldsymbol{A}\}^2 &= {}^1/\sqrt{N}(a_1 \cos\phi_1 + a_2 \cos\phi_2 + \ldots)\times \\
&\qquad {}^1/\sqrt{N}(a_1 \cos\phi_1 + a_2 \cos\phi_2 + \ldots) \\
&= {}^1/N \sum_n \sum_m a_n a_m \cos\phi_n \cos\phi_m. \\
\mathbf{E}[\mathrm{Re}\{\boldsymbol{A}\}^2] &= {}^1/N \sum_n \sum_m \mathbf{E}[a_n a_m]\times \\
&\qquad \mathbf{E}[\cos\phi_n \cos\phi_m] \\
&= {}^1/N \sum_n \mathbf{E}[a_n^2]\mathbf{E}[\cos^2\phi_n]
\end{aligned}
$$

Random phasor sum

$$(\text{since for } n \neq m, \mathbf{E}[\cos\phi_n \cos\phi_m]$$
$$= \mathbf{E}[\cos\phi_n]\mathbf{E}[\cos\phi_m] = 0)$$

$$= {}^1\!/_N \sum\nolimits_n \mathbf{E}[a_n^2] \times \mathbf{E}[{}^1\!/_2 + {}^1\!/_2 \cos 2\phi_n]$$
$$(\text{since } \cos^2\phi = (1+\cos 2\phi)/2)$$

$$= {}^1\!/_N \sum\nolimits_n \mathbf{E}[a_n^2]/2.$$

Similarly, $\sigma^2_{\mathrm{Im}\{\boldsymbol{A}\}} = {}^1\!/_N \sum_n \mathbf{E}[a_n^2]/2.$

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(since for $n \neq m$, $\mathbf{E}[\cos\phi_n\cos\phi_m]$
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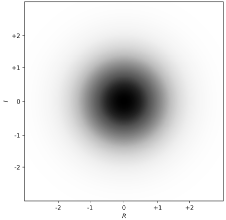
Large numbers

Central Limit Theorem says that the probability density of the *sum* of N independent, identically-distributed, random quantities approaches Normal as $N \to \infty$, ,

$$f_{R,I}(r,i) = \frac{1}{2\pi\sigma^2} \exp\left\{-\frac{r^2+i^2}{2\sigma^2}\right\}$$

Where $R = \mathrm{Re}\{\boldsymbol{A}\}$ and $I = \mathrm{Im}\{\boldsymbol{A}\}$ and $\sigma^2 = \sigma_R^2 = \sigma_I^2$. [cf. SCFT p. 125.]

Large numbers



Normal $f_{R,I}(r, i)$, $[0, 1]$.

Large numbers

Through transformation of variables,* marginal statistics for A and θ are found as Rayleigh and Uniform respectively,

$$f_A(a) = {}^{a}/_{\sigma^2} \exp\left\{ \frac{a^2}{2\sigma^2} \right\}$$

$$f_\theta(\phi) = {}^{1}/_{2\pi}$$

$$\mathbf{E}[A] = \sqrt{{}^{\pi}/_{2}}\ \sigma, \ \ \sigma_A = (2 - {}^{\pi}/_{2})\sigma^2$$

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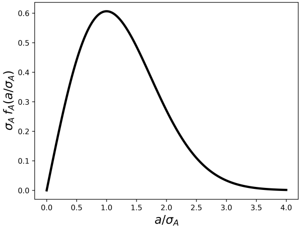

Rayleigh $f_A(a)$, $[0, 1]$ (scaled by σ_A.)

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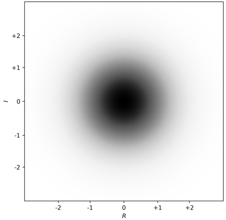

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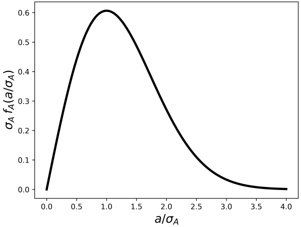

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