

Complex
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Lecture 12

ECE 278 Mathematics for MS Comp Exam

- A *complex gaussian random variable* $\underline{z} = \underline{x} + iy$ has components \underline{x} and \underline{y} described by a real bivariate gaussian random variable $(\underline{x}, \underline{y})$.
- A *complex gaussian random vector* denoted as $\underline{\mathbf{z}} = \underline{\mathbf{x}} + iy$ has components \underline{z}_k described by a real bivariate gaussian random variable $(\underline{x}_k, \underline{y}_k)$.
- A complex gaussian random variable $\underline{z} = \underline{x} + iy$ with independent, zero-mean components \underline{x} and \underline{y} of equal variance is a circularly-symmetric gaussian random variable.

- The corresponding probability density function is called a complex circularly-symmetric gaussian probability density function.
- A complex circularly-symmetric gaussian random variable has the property that $e^{i\theta} \underline{z}$ has the same probability density function for all θ .
- Generalizing, a complex, jointly gaussian random vector $\underline{z} = \underline{x} + i\underline{y}$ is circularly symmetric when the vector $e^{i\theta} \underline{z}$ has the same multivariate probability density function for all θ .
- Such a probability density function must have a zero mean.

- The multivariate probability density function for a complex circularly-symmetric gaussian random vector $\underline{\mathbf{z}}$ is

$$f_{\underline{\mathbf{z}}}(\mathbf{z}) = \frac{1}{\pi^N \det \mathbf{W}} e^{-\mathbf{z}^H \mathbf{W}^{-1} \mathbf{z}}. \quad (1)$$

- Using the properties of determinants, the leading term $(\pi^N \det \mathbf{W})^{-1}$ in (1) can be written as $\det(\pi \mathbf{W})^{-1}$.
- The term \mathbf{W} in (1) is the autocovariance matrix given by

$$\mathbf{W} \doteq \langle \underline{\mathbf{z}} \underline{\mathbf{z}}^H \rangle \quad (2)$$

with H denoting the complex conjugate transpose.

- Because $\underline{\mathbf{z}}$ is complex, this matrix is hermitian.

- The **complex covariance matrix** for this block, can be written as

$$\begin{aligned} \mathbf{W}_{\text{noise}} &= \langle \underline{\mathbf{n}} \underline{\mathbf{n}}^H \rangle \\ &= 2\sigma^2 \mathbf{I}, \end{aligned} \quad (3)$$

where \mathbf{I} is the M by M identity matrix.

- The corresponding probability density function is

$$f(\mathbf{n}) = \frac{1}{(2\pi\sigma^2)^M} e^{-|\mathbf{n}|^2/2\sigma^2}, \quad (4)$$

where $|\mathbf{n}|^2 = \sum_{k=1}^M |n_k|^2 = \sum_{k=1}^M (x_k^2 + y_k^2)$ is the squared euclidean length of the random complex vector $\underline{\mathbf{n}}$.

- Start with components are independent with the corresponding bivariate gaussian density function given by

$$\begin{aligned} f(x, y) &= f_{\underline{x}}(x)f_{\underline{y}}(y) \\ &= \left(\frac{1}{\sqrt{2\pi}\sigma} e^{-x^2/2\sigma^2} \right) \left(\frac{1}{\sqrt{2\pi}\sigma} e^{-y^2/2\sigma^2} \right). \end{aligned} \quad (5)$$

- The two marginal probability density functions are both gaussian with the same variance.
- The two samples described by this joint distribution are independent.

- For a magnitude/phase representation of a circularly-symmetric gaussian, the probability density function of the magnitude $f(A)$ can be obtained by a change of variables using $P = A^2/2$ and $dP/dA = A$, where the factor of $1/2$ accounts for the passband signal.

- This variable transformation yields

$$f(A) = \frac{A}{\sigma^2} e^{-A^2/2\sigma^2} \quad \text{for } A \geq 0. \quad (6)$$

- This is the distribution $f(A)$ for the magnitude
- It is a Rayleigh probability density function

- Similarly, the probability density function $f(\phi)$ for the phase is a uniform probability density function $f(\phi) = (1/2\pi)\text{rect}(\phi/2\pi)$.
- The joint probability density function of these two independent (polar) components is

$$f(A, \phi) = \underline{f}_A(A) \underline{f}_\phi(\phi) = \frac{A}{2\pi\sigma^2} e^{-A^2/2\sigma^2} \quad \text{for } A \geq 0. \quad (7)$$

- Transforming from polar coordinates to cartesian coordinates recovers (5).

- A Poisson random counting process is shown in Figure 1b.
- It is characterized by a **arrival rate** $\mu(t)$.

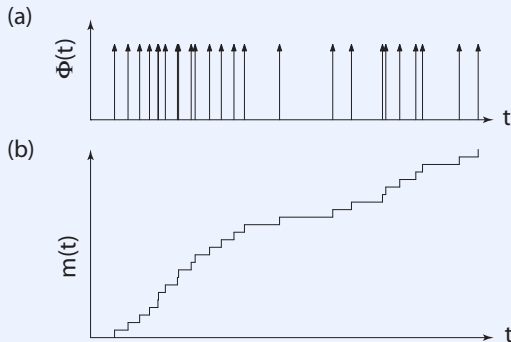


Figure: (a) A realization of a random photoelectron arrival process $g(t)$. (b) The integral of $g(t)$ generates the Poisson counting process $m(t)$.

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- A distinguishing feature of a Poisson counting process is that the number of counts in two nonoverlapping intervals are statistically independent for any size or location of the two intervals.
- This property is called the *independent-increment property* .

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- The probability p_d of generating an event in subinterval Δt is proportional to the product of a **arrival rate** μ and the interval Δt .
- The subinterval Δt can be chosen small enough so that the probability of generating one counting event within Δt is, to within order Δt , given by

$$p_d = \mu \Delta t = \frac{\mu T}{M} = \frac{W}{M}, \quad (8)$$

where $W = \mu T$ is the mean number of counts over an interval $T = M \Delta t$.

- The probability that no counts are generated within an interval of duration Δt is, to order Δt , $1 - \mu \Delta t$.

- The probability of generating m independent counts within a time $T = M\Delta t$ is given by a **binomial probability mass function**

$$p(m) = \frac{M!}{m!(M-m)!} (p_d)^m (1-p_d)^{M-m} \quad \text{for } m = 0, 1, 2, \dots, M.$$

- Substituting $p_d = W/M$ from (8) yields

$$\begin{aligned} p(m) &= \frac{M!}{M^m (M-m)!} \frac{W^m}{m!} \left(1 - \frac{W}{M}\right)^{M-m} \\ &= \frac{M(M-1)\dots(M-m+1)}{M^m} \frac{W^m}{m!} \left(1 - \frac{W}{M}\right)^{M-m}. \end{aligned} \quad (9)$$

- Referring to (8), if μ and T are both held fixed, then W is constant.

- Therefore, in the limit as $W/M = \mu\Delta t$ goes to zero, M goes to infinity.
- The first term in (9) approaches one because the numerator approaches M^m .
- In the last term, the finite value of m relative to the value of M can be neglected.
- This produces $(1 - W/M)^M$ which goes to e^{-W} as M goes to infinity.
- Therefore, the probability mass function of the number of counts generated over an interval T is

$$p(m) = \frac{W^m}{m!} e^{-W} \quad \text{for } m = 0, 1, 2, \dots \quad (10)$$

which is the **Poisson probability distribution** (or the Poisson probability mass function) with the mean $\langle \underline{m} \rangle$ given by $\mu T = W$.

- The variance of the Poisson probability distribution can be determined using the characteristic function

$$C_m(\omega) = \sum_{m=0}^{\infty} e^{i\omega m} p(m) = \sum_{m=0}^{\infty} e^{i\omega m} \frac{W^m}{m!} e^{-W}$$

- The summation has the form $\sum_{m=0}^{\infty} \frac{1}{m!} x^m = e^x$ with $x = We^{i\omega}$. Then $C_m(\omega)$ reduces as

$$C_m(\omega) = e^{W(e^{i\omega} - 1)}. \quad (11)$$

- From Lecture 12, the mean-squared value in terms of the characteristic function is

$$\begin{aligned}\langle \underline{m}^2 \rangle &= \left. \frac{1}{i^2} \frac{d^2}{d\omega^2} C_m(\omega) \right|_{\omega=0} \\ &= e^{W(e^{i\omega}-1)} \left(W e^{i\omega} + (W e^{i\omega})^2 \right) \Big|_{\omega=0} \\ &= W + W^2.\end{aligned}\tag{12}$$

- Accordingly

$$\sigma_m^2 = \langle \underline{m}^2 \rangle - \langle \underline{m} \rangle^2 = W\tag{13}$$

is the variance of the Poisson distribution.

- Expression (13) shows that the variance σ_m^2 is equal to the mean.
- A random variable described by the Poisson probability distribution is called a **Poisson random variable**.
- The sum of two independent Poisson random variables \underline{m}_1 and \underline{m}_2 is a Poisson random variable \underline{m}_3 .
- Let $p_1(m)$ and $p_2(m)$ be two Poisson probability distributions with mean values W_1 and W_2 respectively. Then the probability distribution $p_3(m)$ for \underline{m}_3 is the convolution $p_3(m) = p_1(m) \circledast p_2(m)$.

- The convolution property of a Fourier transform states that the two characteristic functions satisfy

$$C_3(\omega) = C_1(\omega)C_2(\omega),$$

where $C_i(\omega)$ is the characteristic function of $p_i(m)$.

- Substitute $C_1(\omega) = e^{W_1(e^{i\omega} - 1)}$ and $C_2(\omega) = e^{W_2(e^{i\omega} - 1)}$ on the right (cf. (11)) and take the inverse Fourier transform to give

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$$p_3(m) = \frac{(W_1 + W_2)^m}{m!} e^{-(W_1 + W_2)} \quad \text{for } m = 0, 1, 2, \dots \quad (14)$$

- Accordingly, the sum of two independent Poisson random variables with means W_1 and W_2 respectively, is a Poisson random variable with a mean $W_1 + W_2$.

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- The probability density function for the waiting time t_1 to observe one event of a Poisson process from any starting time is denoted $f(t_1)$.
- For a Poisson stream, this probability density function does not depend on the starting time.
- For a constant arrival rate μ , the cumulative probability density function of the random arrival time \underline{t}_1 is equal to $1 - p_0$ where p_0 is the probability that no counts are generated over the interval t_1 .

- The probability p_0 is determined using the Poisson probability distribution defined in (10) with $W = \mu t_1$ and $m = 0$. This yields $p_0 = e^{-\mu t_1}$.

- The cumulative probability density function is

$$F(t_1) = 1 - e^{-\mu t_1} \quad \text{for } t_1 \geq 0.$$

- The corresponding probability density function is determined using (see Lecture 11)

$$\begin{aligned} f(t_1) &= \frac{d}{dt} F(t_1) \\ &= \mu e^{-\mu t_1} \quad \text{for } t_1 \geq 0, \end{aligned} \quad (15)$$

which is an exponential probability density function with mean μ^{-1} and variance μ^{-2} .

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- Given that the count events are independent, the waiting time for the second photoelectron event, and each subsequent event, is an independent exponential probability density function.
- The probability density function of the waiting time to generate k photoelectrons is the sum of k independent, exponentially distributed random variables—one random variable for each photoelectron arrival, and each with the same expected value μ^{-1} .
- This is a ***gamma probability density function*** with parameters (μ, k) .