

## CM10-230328Tue

### Announcements

1. Midterm exam is approaching
2. HW#8 is assigned and due at 10:59am on Thu. Mar. 30th. HW#9 will be assigned soon.
3. Handouts, annotated handouts are available at <http://cisl.postech.ac.kr/class/eece574/schedule.htm> . Passwords are ...
4. Lecture videos are available at cisl.postech YouTube channel. Clickable time stamps, please.

Corrections; Clarifications; Common mistakes, misunderstandings, misconceptions, myth; Frequently Asked Questions; Conventional wisdom

1.

Overview w/ Chapter numbers from the main textbook by Papoulis, (2)-(7) from Peebles

#### 9. General Concepts

1. RP concept
- (2) Stationarity and Independence
- (5) Gaussian RPs
- (6) Poisson RPs
- (7) Complex RPs
- (2) Time average and Ergodicity
- (3) Correlation functions
- (4) Measurement of correlation functions

#### 7. Sequence of Random Variables

##### 9.1

- positive semi-definiteness of a correlation function
- alpha-dependent random process
- correlation alpha-dependent random process
- white noise in terms of correlation function
- mean-square periodic random process
- cyclostationary random process

#### 10. Random Walks and Other Applications

##### 11. Spectral Representation

##### 12. Spectrum Estimation

##### 13. Mean-Square Estimation

### Review

1. a complex random vector
  - a. Def.
  - b. CDF, PDF
  - c. mean vector, covariance and pseudo-covariance matrices
  - d. propriety vs. impropriety
  - e. proper-complex Gaussian random vector
    - i. PDF

### Preview

1. proper-complex Gaussian random vector
  - a. CDF of norm
    - i. Marcum's Q function
    - ii. generalized Marcum's Q function
    - iii. cf) chi-square distribution
  - b. a complex random process
  - c. why?
  - d. a complex-valued vector random process
  - e. widely-linear processing
2. Time average and ergodicity

1-D

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# Gaussian distributions for communication engineering

$X \sim N(0,1)$

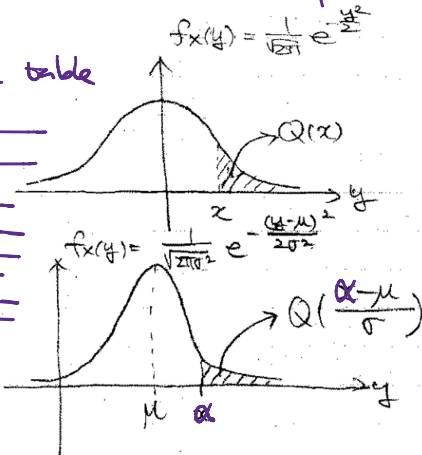
Definition

$$Q(x) \triangleq \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-\frac{y^2}{2}} dy$$

No closed-form expression

Tabulate  
= make a table

| x | Q(x) |
|---|------|
| 0 |      |
| 1 |      |
| 2 |      |
| 3 |      |



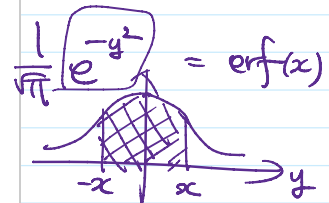
$X \sim N(\mu, \sigma^2)$

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

$$Y = \frac{X-\mu}{\sigma}$$

$$F_X(x) = P(X \leq x) = Q\left(\frac{x-\mu}{\sigma}\right)$$

$Z = 10Y + 60$   
 $Z \sim N(60, 10^2)$



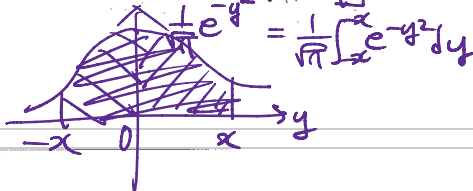
$\text{erfc}(x) = 1 - \text{erf}(x)$

The integral is not an elementary integral. Hence,  $F(x) = 1 - Q(x)$  and  $\text{erf}(x)$  are distribution function of  $X$

MATLAB built-in

widely tabulated, where

$\text{erf}(x) \triangleq \frac{2}{\sqrt{\pi}} \int_0^x e^{-y^2} dy$  (error ft)



6

$\text{erfc}(x) = 1 - \text{erf}(x)$  (complementary error ft)

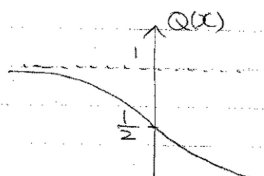
Note

$$Q(x) = \frac{1}{2} \left\{ 1 - \text{erf}\left(\frac{x}{\sqrt{2}}\right) \right\}$$

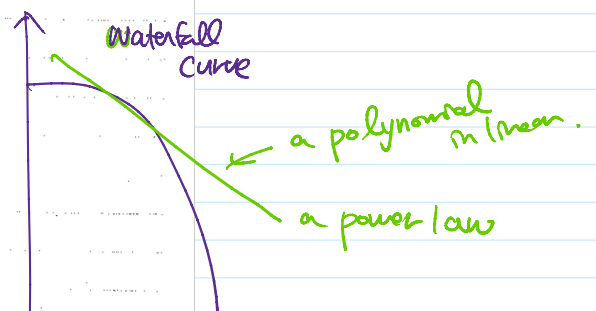
$$= \frac{1}{2} \text{erfc}\left(\frac{x}{\sqrt{2}}\right)$$

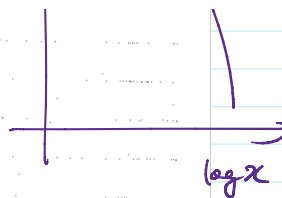
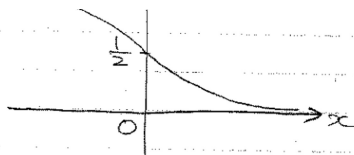
Properties as a function

(0) (0th order derivative)



$(\log Q(x))$





• a power law

$$0 < Q(x) < 1, \forall x \in \mathbb{R}$$

$$Q(x) + Q(-x) = 1, \forall x \in \mathbb{R} \quad (\Rightarrow Q(0) = \frac{1}{2})$$

(i) (1st order derivative)

$$Q'(x) = -\frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} < 0 \quad \forall x \in \mathbb{R}$$

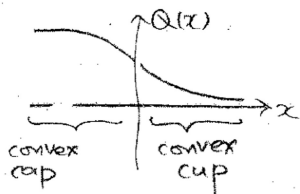
(monotonically decreasing)

(ii) (2nd order derivative)

$$Q''(x) = \frac{x}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

$$Q''(x) > 0 \quad \text{for} \quad x > 0 \quad (\text{convex cup})$$

$$Q''(x) < 0 \quad \text{for} \quad x < 0 \quad (\text{convex cap})$$



(← Figure. Wozencraft PB3. 'Gaussian' Log scale in y-axis)

$$\begin{cases} Q(x) \\ Q'(x) \\ Q''(x) \end{cases}$$

$$\begin{cases} Q(\frac{1}{\sqrt{x}}) \\ -Q'(\frac{1}{\sqrt{x}}) \\ Q''(\frac{1}{\sqrt{x}}) \end{cases}$$

Since

$$0 < \int_a^\infty \frac{1}{\beta^2} e^{-\beta^2/2} d\beta < \frac{1}{\alpha^3} \int_a^\infty \beta e^{-\beta^2/2} d\beta = \frac{1}{\alpha^3} e^{-\alpha^2/2},$$

we have the bounds

$$\frac{1}{\sqrt{2\pi\alpha}} e^{-x^2/2} \left(1 - \frac{1}{\alpha^2}\right) < Q(\alpha) < \frac{1}{\sqrt{2\pi\alpha}} e^{-\alpha^2/2}, \quad \alpha > 0. \quad (2.121)$$

These two bounds are plotted together with  $Q(\alpha)$  in Fig. 2.36.

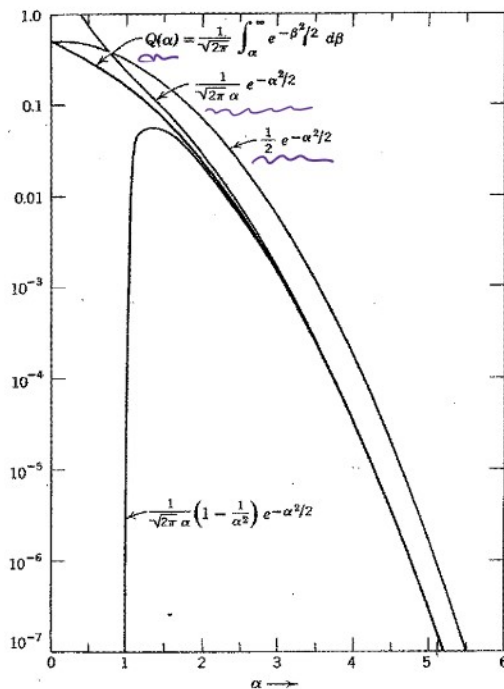


Figure 2.36 The function  $Q(\alpha)$  and three bounds.

loose

"an upper bound is tight"

$$\underline{f(x) \leq g(x)}, \forall x > 0$$

$$\begin{matrix} X \sim N(0,1) \\ Y \sim N(0,1) \end{matrix} \text{ indep.}$$

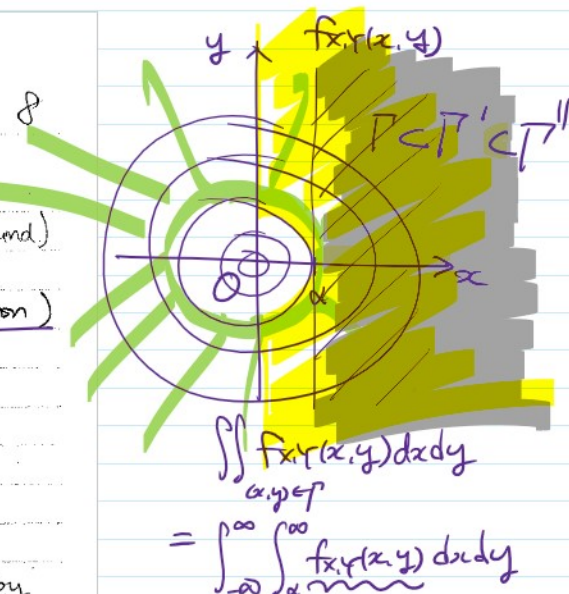
- Upper and lower bounds on  $Q(x)$

(i)  $Q(x) \leq e^{-\frac{x^2}{2}}$  (a Chernoff bound)

(ii)  $Q(x) \leq \frac{1}{2} e^{-\frac{x^2}{2}}$  (220) (2-D integration)

In (ii), the equality holds iff  $x=0$

$$(ii) \quad \frac{1}{\sqrt{2\pi}} \left(1 - \frac{1}{x^2}\right) \frac{e^{-\frac{x^2}{2}}}{x} < Q(x) < \frac{1}{\sqrt{2\pi}} \frac{e^{-\frac{x^2}{2}}}{x} \quad \text{for } x > 0 \quad (\text{Integration by})$$



$$\frac{1}{\sqrt{2\pi}} \left(1 - \frac{1}{x^2}\right) \frac{1}{x} < Q(x) < \frac{1}{\sqrt{2\pi}} \frac{1}{x} \quad \text{for } x > 0 \quad (\text{Integration by parts})$$

- Comparison of two upper bounds

$\frac{1}{\sqrt{2\pi}} \frac{e^{-x^2/2}}{x}$  is tighter than  $\frac{1}{2} e^{-x^2/2}$  for

$$\left( \frac{\sqrt{2}}{\pi} < x \right)$$

$\frac{1}{2} e^{-x^2/2}$  is tighter than  $\frac{1}{\sqrt{2\pi}} \frac{e^{-x^2/2}}{x}$  for

$$0 \leq x < \sqrt{\frac{2}{\pi}} (\approx 0.7979) \quad (\leftarrow \text{See Weizenkraft Figure 2.36})$$

However, actually, both are inaccurate.

- Approximation for  $Q(x)$

(i)  $\text{erfc}(x)$  can be represented by a Taylor series in terms of the Hermite polynomial.

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx dy$$

$$= \int_{-\infty}^{\infty} f_Y(y) dy \int_{-\infty}^{\infty} f_X(x) dx$$

$$= 1 \cdot Q(x)$$

$$Q(x) \leq \iint_{\mathcal{R}'} f_{X,Y}(x,y) dx dy$$

$$= \frac{1}{2} \iint_{\mathcal{R}'} f_{X,Y}(x,y) dx dy =$$

$$= \frac{1}{2} e^{-\frac{x^2}{2}}, \quad \forall x \geq 0$$

of degree  $(k-1)$  as

$$\frac{d^k}{dx^k} \operatorname{erfc}(x) = (-1)^k \frac{2}{\sqrt{\pi}} H_{k-1}(x) e^{-x^2}$$

(ii) Alternative expression for  $Q(x)$  is given by

$$Q(x) = \frac{1}{\pi} \int_0^{\frac{\pi}{2}} \exp\left(-\frac{x^2}{2 \sin^2 \theta}\right) d\theta, \quad (x > 0)$$

$\begin{array}{l} \text{proper} \\ \text{integral} \\ \text{improper} \end{array}$ 

$$\left( = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp\left(-\frac{y^2}{2}\right) dy \right)$$

Numerical integration / required

(iii)  $n$ -th order approximation of  $Q(x)$

$$Q(x) \approx Q_n(x) = \frac{1}{\sqrt{2\pi}} x e^{-\frac{x^2}{2}} \times \left\{ 1 + \sum_{k=1}^n (-1)^k \frac{1 \cdot 3 \cdot 5 \cdots (2k-1)}{x^{2k}} \right\} \quad \text{for } x > 0$$

- Property of  $Q(\sqrt{2}x)$  for  $x > 0$ .

(i)  $Q'(\sqrt{2}x) < 0$  for  $x > 0$       monotonically decreasing

(ii)  $Q''(\sqrt{2}x) > 0$  for  $x > 0$       convex cup fit

(sol)

$$Q'(\sqrt{2}x) = -\frac{1}{\sqrt{2\pi}} e^{-x^2} \frac{1}{\sqrt{2}x}$$

$$Q''(\sqrt{2}x) = \frac{1}{\sqrt{2\pi}} e^{-x^2} \frac{1}{\sqrt{2}x} \left( 1 + \frac{1}{2x^2} \right)$$

No can use Jensen's Ineq. (M)

$$E[Q(X)]$$

$$= E \left[ \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy \right]$$

$$= E \left[ \frac{1}{\pi} \int_0^{\frac{\pi}{2}} \exp\left(-\frac{x^2}{2 \sin^2 \theta}\right) d\theta \right]$$

The exponential family

1D  
2D

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$$\begin{bmatrix} X \\ Y \end{bmatrix} \sim N \left( \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}, \sigma^2 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right)$$

- When  $\mu_x = \mu_y = 0$

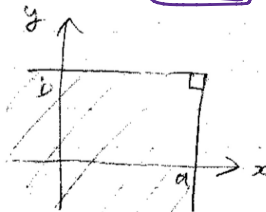
(i) Cartesian coordinate

$$\begin{aligned} f_{X,Y}(x,y) &= \frac{1}{\sqrt{2\pi}^2 \sqrt{\det(\sigma^2 I)}} \exp\left(-\frac{1}{2} [x \ y] (\sigma^2 I)^{-1} \begin{bmatrix} x \\ y \end{bmatrix}\right) \\ &= \frac{1}{2\pi \sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \\ &= \underbrace{\frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right)}_{f_X(x)} \underbrace{\frac{1}{\sqrt{2\pi} \sigma} \exp\left(-\frac{y^2}{2\sigma^2}\right)}_{f_Y(y)} \\ &= f_X(x) \times f_Y(y) \end{aligned}$$

$\Rightarrow X$  &  $Y$  are independent



$$\begin{aligned} \text{ex/ } \Pr(X \leq a, Y \leq b) &= \Pr(X \leq a) \Pr(Y \leq b) \\ &= \left\{1 - Q\left(\frac{a}{\sigma}\right)\right\} \left\{1 - Q\left(\frac{b}{\sigma}\right)\right\} \end{aligned}$$



(ii) Polar coordinate

If we rotate by

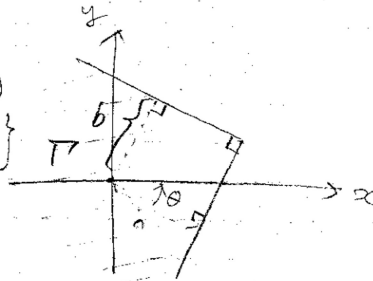
$$\begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix}$$

then

$$\begin{aligned} f_{X,Y}(\tilde{x}, \tilde{y}) &= f_{X,Y}(\tilde{x} \cos \theta + \tilde{y} \sin \theta, -\tilde{x} \sin \theta + \tilde{y} \cos \theta) \\ &= \frac{1}{2\pi\sigma^2} \exp\left(-\frac{1}{2\sigma^2} \left\{ (\tilde{x} \cos \theta + \tilde{y} \sin \theta)^2 + (-\tilde{x} \sin \theta + \tilde{y} \cos \theta)^2 \right\}\right) \\ &= \frac{1}{2\pi\sigma^2} \exp\left(-\frac{\tilde{x}^2 + \tilde{y}^2}{2\sigma^2}\right) \\ &= f_{X,Y}(\tilde{x}, \tilde{y}) \quad \forall \theta \in [0, 2\pi) \end{aligned}$$

$\Rightarrow$  rotationally invariant distribution  
 $\equiv$  circularly symmetric distribution

$$\begin{aligned} \text{ex/ } \Pr((X,Y) \in \Gamma) &= \Pr(\tilde{X} \leq a, \tilde{Y} \leq b) \\ &= \left[1 - \Phi\left(\frac{a}{\sigma}\right)\right] \left[1 - \Phi\left(\frac{b}{\sigma}\right)\right] \end{aligned}$$



In the polar coordinate,

$$\begin{aligned} f_{R,\Theta}(r, \theta) &\triangleq f_{X,Y}(r \cos \theta, r \sin \theta) \cdot r \\ &= \frac{r}{2\pi\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right), \quad r \geq 0, \quad 0 \leq \theta < 2\pi \end{aligned}$$

where  $R = \sqrt{X^2 + Y^2}$ ,  $\Theta = \tan^{-1} \frac{Y}{X}$

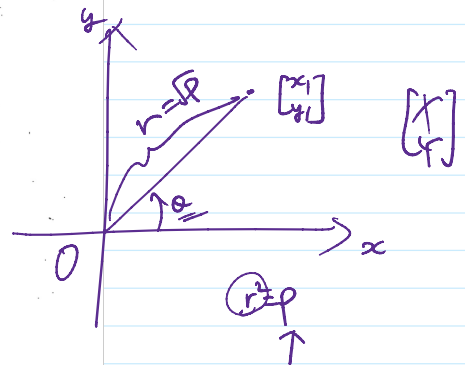
$$= \frac{1}{2\pi} \cdot \frac{r}{\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right)$$

$$= f_{\Theta}(\theta) \times f_R(r)$$

$\Rightarrow \Theta$  and  $R$  are independent.

$\uparrow$  uniform random variable on  $[0, 2\pi)$

$\uparrow$  Rayleigh random variable w/ parameter  $\sigma^2$

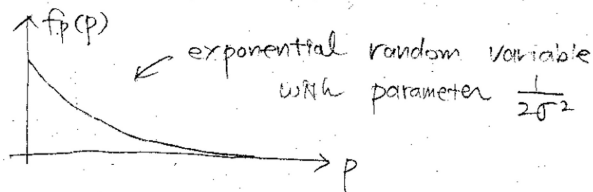


As we've seen  $f_{R,\Theta}(r,\theta)$  is not a function of  $\theta$ . (circularly symmetric!)

Let  $P \triangleq R^2$ , then

$$f_P(p) = \frac{1}{2\sqrt{p}} f_R(\sqrt{p})$$

$$= \frac{1}{2\sigma^2} \exp\left(-\frac{p}{2\sigma^2}\right), \quad p \geq 0$$

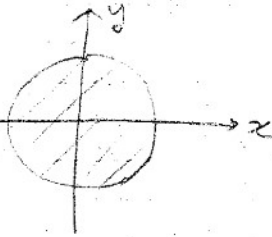


$$\text{lex/ } \Pr(\sqrt{x^2 + y^2} \leq c) \\ = \Pr(R \leq c)$$

$$= \int_0^c \frac{r}{\sigma^2} \exp\left(-\frac{r^2}{2\sigma^2}\right) dr$$

$$= \left[ -\exp\left(-\frac{r^2}{2\sigma^2}\right) \right]_0^c$$

$$= 1 - \exp\left(-\frac{c^2}{2\sigma^2}\right)$$



Now, let's show

$$Q(x) = \int_0^{\frac{\pi}{2}} \frac{1}{\pi} \exp\left(-\frac{x^2}{2\sin^2\theta}\right) d\theta, \quad x \geq 0$$

and

$$Q(x) \leq \frac{1}{2} \exp\left(-\frac{x^2}{2}\right), \quad x \geq 0$$

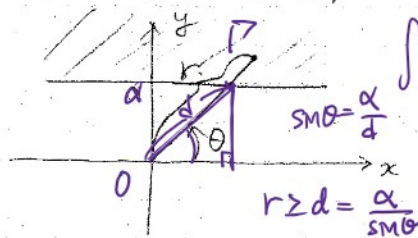
Note that

$$Q(a) = \Pr(Y \geq a, -\infty < X < \infty)$$

where

$$\begin{bmatrix} X \\ Y \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right)$$

Hence,

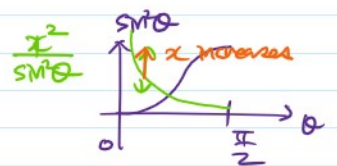


$$Q(a) = \Pr(R \sin\theta \geq a, 0 < \theta < \pi)$$

$$\iint_{\Gamma} f_X Y(x, y) dx dy = Q(a) = \int_0^{\pi} \int_{\frac{a}{\sin\theta}}^{\infty} f_X Y(r \cos\theta, r \sin\theta) r dr d\theta$$

$$\Gamma = \{(x, y) : x \in \mathbb{R}, y \geq a\} \\ = \{(r, \theta) : 0 < \theta < \pi, r \geq \frac{a}{\sin\theta}\}$$

$$= 2 \int_0^{\frac{\pi}{2}} \int_{\frac{a}{\sin\theta}}^{\infty} \frac{1}{2\pi} \frac{r}{r} e^{-\frac{r^2}{2}} dr d\theta$$



$$= \int_0^{\pi} \int_{\frac{a}{\sin\theta}}^{\infty} \frac{r}{2\pi} \exp\left(-\frac{r^2}{2}\right) dr d\theta$$

$$= \int_0^{\pi} \frac{1}{2\pi} \exp\left(-\frac{a^2}{2\sin^2\theta}\right) d\theta$$

$$Q(x) = \int_0^{\frac{\pi}{2}} \frac{1}{\pi} \exp\left(-\frac{a^2}{2\sin^2\theta}\right) d\theta$$

$$\text{Since } \sin^2\theta \leq 1$$

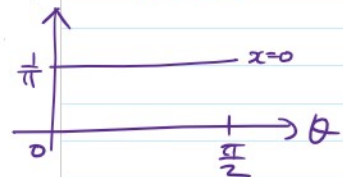
$$\Rightarrow \frac{1}{\sin^2\theta} \geq 1$$

$$\Rightarrow -\frac{x^2}{2\sin^2\theta} \leq -\frac{x^2}{2}$$

$$\Rightarrow \exp\left(-\frac{x^2}{2\sin^2\theta}\right) \leq \exp\left(-\frac{x^2}{2}\right)$$

$$\Rightarrow Q(x) < \int_0^{\frac{\pi}{2}} \frac{1}{\pi} \exp\left(-\frac{x^2}{2}\right) d\theta \quad x > 0$$

$$Q(x) = \int_0^{\frac{\pi}{2}} \frac{1}{\pi} \exp\left(-\frac{x^2}{2\sin^2\theta}\right) d\theta$$

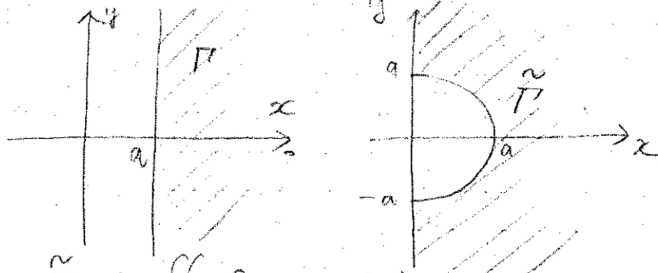


$$\Rightarrow \exp\left(-\frac{x^2}{2\sin^2\theta}\right) \leq \exp\left(-\frac{x^2}{2}\right)$$

$$\Rightarrow Q(x) \leq \int_0^{\frac{\pi}{2}} \frac{1}{\pi} \exp\left(-\frac{x^2}{2}\right) d\theta, \quad x \geq 0$$

$$\Rightarrow Q(x) \leq \frac{1}{2} \exp\left(-\frac{x^2}{2}\right), \quad x \geq 0$$

This can be shown as follows, too.



$$P \subset \tilde{P} \Rightarrow \iint_P f(x,y) dx dy \leq \iint_{\tilde{P}} f(x,y) dx dy$$

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$$\Rightarrow Q(x) \leq \Pr\left(R \geq x, -\frac{\pi}{2} \leq \theta \leq \frac{\pi}{2}\right)$$

$$= \frac{1}{2} \Pr(R \geq x)$$

$$= \frac{1}{2} \exp\left(-\frac{x^2}{2}\right), \quad x \geq 0$$

- When  $(\mu_x, \mu_y) \neq (0, 0)$

(i) Cartesian coordinate

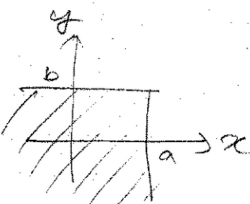
$$f_{X,Y}(x,y) = \underbrace{\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu_x)^2}{2\sigma^2}\right)}_{f_X(x)} \times \underbrace{\frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y-\mu_y)^2}{2\sigma^2}\right)}_{f_Y(y)}$$

$\Rightarrow X$  &  $Y$  are independent

lex/  $\Pr(X \leq a, Y \leq b)$

$$= \Pr(X \leq a) \Pr(Y \leq b)$$

$$= \left\{1 - Q\left(\frac{a-\mu_x}{\sigma}\right)\right\} \left\{1 - Q\left(\frac{b-\mu_y}{\sigma}\right)\right\}$$



(ii) Polar coordinate.

If we rotate with respect to  $\begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$  by

$$\begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} X - \mu_x \\ Y - \mu_y \end{bmatrix} + \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$$

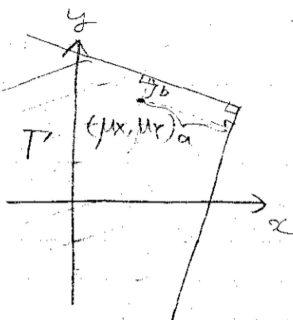
then

$$f_{X,Y}(x,y) = f_{X,Y}((\tilde{x}-\mu_x)\cos\theta + (\tilde{y}-\mu_y)\sin\theta + \mu_x, -(\tilde{x}-\mu_x)\sin\theta + (\tilde{y}-\mu_y)\cos\theta + \mu_y)$$

$$= f_{X,Y}(\tilde{x}, \tilde{y})$$

$\Rightarrow$  circularly symmetric with respect to  $\begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$

$$Pr((X,Y) \in T) \\ = \left\{1 - Q\left(\frac{a}{\sigma}\right)\right\} \left\{1 - Q\left(\frac{b}{\sigma}\right)\right\}$$



In the polar coordinate,

$$f_{R,\Theta}(r,\theta) \triangleq f_{X,Y}(r\cos\theta, r\sin\theta) r$$

$$= \frac{r}{2\pi\sigma^2} \exp\left(-\frac{(r\cos\theta - \mu_x)^2 + (r\sin\theta - \mu_y)^2}{2\sigma^2}\right)$$

$$= \frac{r}{2\pi\sigma^2} \exp\left(-\frac{r^2 + X^2}{2\sigma^2}\right) \exp\left(\frac{r(\mu_x\cos\theta + \mu_y\sin\theta)}{\sigma^2}\right)$$

where  $X \triangleq \sqrt{\mu_x^2 + \mu_y^2}$

Since

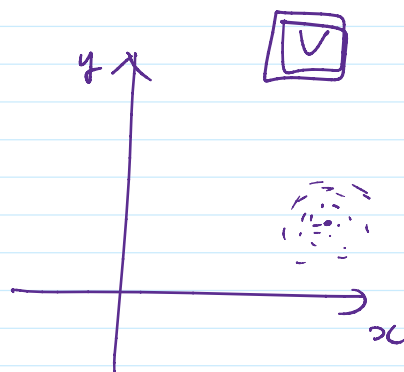
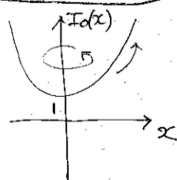
$$f_R(r) = \int_0^{2\pi} f_{R,\Theta}(r,\theta) d\theta$$

$$= \frac{r}{\sigma^2} \exp\left(-\frac{r^2 + X^2}{2\sigma^2}\right)$$

$$\times \frac{1}{2\pi} \int_0^{2\pi} \exp\left(\frac{rX}{\sigma^2} \cos(\theta + \alpha)\right) d\theta$$

$$\triangleq I_0\left(\frac{rX}{\sigma^2}\right)$$

where  $I_0(x) \triangleq \frac{1}{2\pi} \int_0^{2\pi} \exp(x \cos\theta) d\theta$



is called the zero-th order modified Bessel function of the 1st kind.

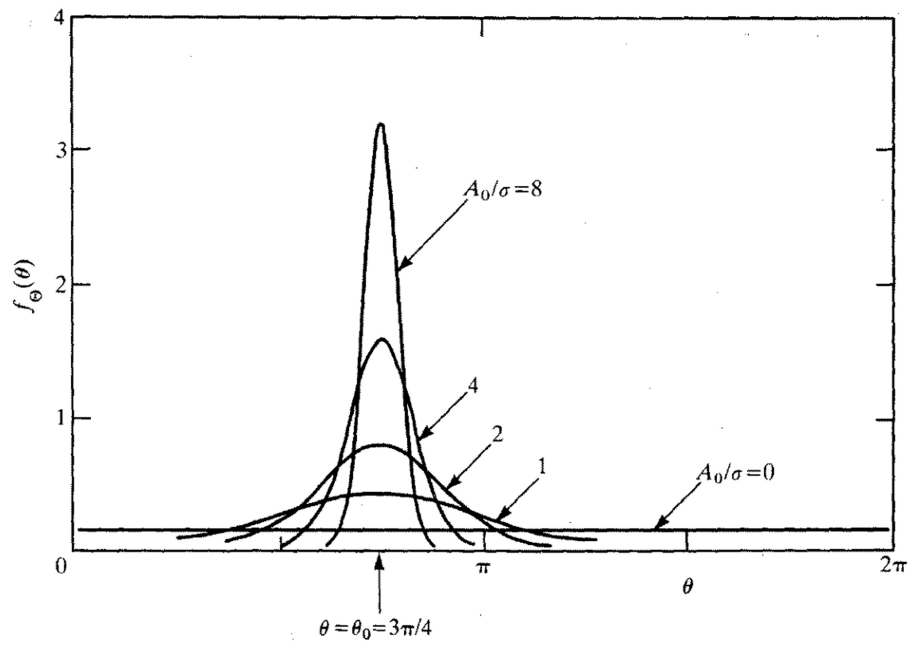
The distribution of  $R$  is a  $\left\{ \begin{array}{l} \text{Ricean} \\ \text{Rician} \end{array} \right\}$  distribution

$$f_{\Theta}(\theta) = \frac{1}{2\pi} \exp\left(-\frac{R^2}{2\sigma^2}\right) + \frac{R \cos(\theta - \theta_0)}{\sqrt{2\pi}\sigma^2} \exp\left(-\frac{R^2 \sin^2(\theta - \theta_0)}{2\sigma^2}\right) \times \left(1 - Q\left(\frac{A_0 \cos(\theta - \theta_0)}{\sigma}\right)\right)$$

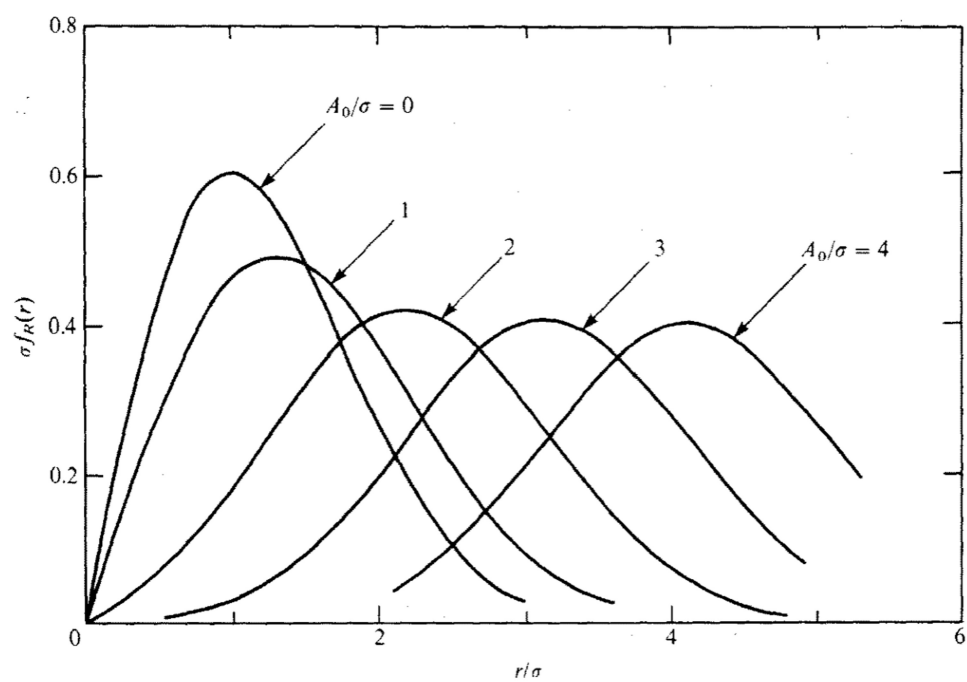
$$\text{where } R = \sqrt{\mu_x^2 + \mu_y^2}$$

$$\theta = \tan^{-1}\left(\frac{\mu_y}{\mu_x}\right)$$

$$\lim_{\frac{R}{\sigma} \rightarrow \infty} f_{\Theta}(\theta) = \delta(\theta - \theta_0)$$

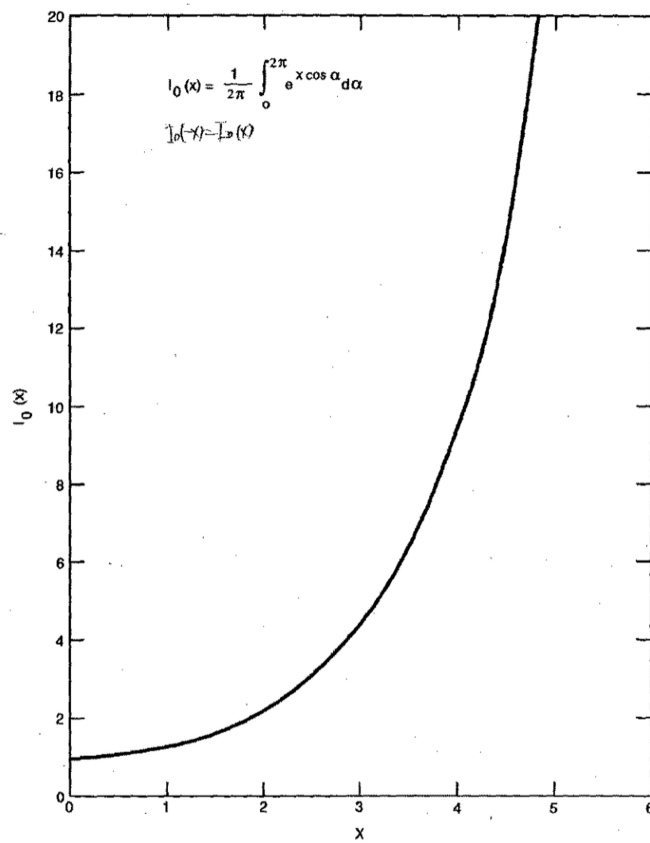


**FIGURE 10.6-2** Probability density function of the phase of the sum of a sinusoidal signal and gaussian noise. Curves are plotted for a signal phase of  $\theta_0 = 3\pi/4$ .



**FIGURE 10.6-1**

Probability densities of the envelope of a sinusoidal signal (amplitude  $A_0$ ) plus noise (power  $\sigma^2$ ) for various ratios  $A_0/\sigma$ .

Figure 5.2 Plot of  $I_0(x)$ 

Hence, using (5.22) in (5.20), the optimum decision rule sets  $\hat{m}(\rho(t)) = m_k$  when

$$I_0\left(\frac{2\xi_i}{N_0}\right) \exp\left(-\frac{E_i}{N_0}\right) \quad (5.23)$$

is maximum for  $k = i$ . Recall from (5.17) that the envelope  $\xi_i$  is given by

$$\xi_i = \sqrt{z_{ci}^2 + z_{si}^2} \quad (5.24)$$