

# 1 Objectives

Calculate mutual information using numerical integration for a complex, linearized signal model  $\vec{z}(\mu, \vec{k})$ .

$$\vec{z}(\mu, \vec{k}) = \int_{\Omega} M(\vec{x}) e^{-s(\mu, \vec{x})} e^{-2\pi i \vec{k} \cdot \vec{x}} d\vec{x} + \nu = \mathcal{G}(\mu, \vec{k}) + \nu \quad \nu \sim \mathcal{N}(\vec{0}, \Sigma_{\nu}) \quad \Sigma_{\nu} = \begin{bmatrix} \sigma_{\nu,r}^2 & 0 \\ 0 & \sigma_{\nu,i}^2 \end{bmatrix} \quad (1)$$

$$s(\mu, \vec{x}) = \frac{T_E}{T_2^*(\vec{x})} + i[2\pi\gamma\alpha B_0 T_E \Delta u(\mu, \vec{x}) + T_E \Delta \omega_0(\vec{x})]$$

Therefore, the probability distribution for  $p(\mathbf{z}|\mu)$  is

$$p(\mathbf{z}|\mu) = \mathcal{N}(\mathcal{G}(\mu), \Sigma_{\nu}) \quad (2)$$

Assume normal distribution for the model parameter, optical attenuation coefficient  $\mu$ .

$$\mu \sim \mathcal{N}(\bar{\mu}, \sigma_{\mu}) \quad (3)$$

## 2 Work

### 2.1 Probability Distribution Definitions

Calculate mutual information using numerical integration for a complex, linearized signal model  $\vec{z}(\mu, \vec{k})$ .

$$\vec{z}(\mu, \vec{k}) = \int_{\Omega} M(\vec{x}) e^{-s(\mu, \vec{x})} e^{-2\pi i \vec{k} \cdot \vec{x}} d\vec{x} + \nu = \mathcal{G}(\mu, \vec{k}) + \nu \quad \nu \sim \mathcal{N}(\vec{0}, \Sigma_{\nu}) \quad \Sigma_{\nu} = \begin{bmatrix} \sigma_{\nu,r}^2 & 0 \\ 0 & \sigma_{\nu,i}^2 \end{bmatrix} \quad (4)$$

$$s(\mu, \vec{x}) = \frac{T_E}{T_2^*(\vec{x})} + i[2\pi\gamma\alpha B_0 T_E \Delta u(\mu, \vec{x}) + T_E \Delta \omega_0(\vec{x})]$$

Therefore, the probability distribution for  $p(\mathbf{z}|\mu)$  is

$$p(\mathbf{z}|\mu) = \mathcal{N}(\mathcal{G}(\mu), \Sigma_{\nu}) \quad (5)$$

Assume normal distribution for the model parameter, optical attenuation coefficient  $\mu$ .

$$\mu \sim \mathcal{N}(\bar{\mu}, \sigma_{\mu}) \quad (6)$$

Also of note, because the real and imaginary components of  $z$  are assumed independent, the covariance matrix  $\Sigma_z$  is diagonal, and the following simplification results.

$$p(\mathbf{z}|\mu) = \mathcal{N}_{\mathbf{z}}(\mathcal{G}(\mu), \Sigma_{\nu}) = \mathcal{N}_{z_r}(\mathcal{G}_r(\mu), \sigma_{\nu}) \mathcal{N}_{z_i}(\mathcal{G}_i(\mu), \sigma_{\nu}) = p(z_r|\mu) p(z_i|\mu) \quad (7)$$

### 2.2 Problem Statement

The most approachable way to solve mutual information is to begin with the difference of entropies definition.

$$I(\mu; z) = H(z) - H(z|\mu) = \frac{1}{2} \ln \left( (2\pi e)^2 \cdot |\Sigma_z| \right) - \frac{1}{2} \ln \left( (2\pi e)^2 \cdot |\Sigma_{\nu}| \right) \quad (8)$$

Assuming  $\sigma_{\nu,r}^2 = \sigma_{\nu,i}^2$ , then

$$|\Sigma_{\nu}| = \sigma_{\nu}^2 \sigma_{\nu}^2 - 0 = \sigma_{\nu}^4 \quad (9)$$

Calculation of  $\Sigma_z$  is less straightforward.

$$\Sigma_z = \begin{bmatrix} \mathbb{E} \left[ (z_r - \mathbb{E}[z_r])^2 \right] & \mathbb{E} [(z_r - \mathbb{E}[z_r]) (z_i - \mathbb{E}[z_i])] \\ \mathbb{E} [(z_i - \mathbb{E}[z_i]) (z_r - \mathbb{E}[z_r])] & \mathbb{E} \left[ (z_i - \mathbb{E}[z_i])^2 \right] \end{bmatrix} \quad (10)$$

$\mathbb{E}[z_r]$ ,  $\mathbb{E}[z_i]$ ,  $\mathbb{E}[(z_r - \mathbb{E}[z_r])^2]$ ,  $\mathbb{E}[(z_i - \mathbb{E}[z_i])^2]$ , and  $\mathbb{E}[(z_r - \mathbb{E}[z_r]) (z_i - \mathbb{E}[z_i])]$  all need to be calculated numerically. As one example of this process, take  $\mathbb{E}[z_r]$ :

$$\mathbb{E}[z_r] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z_r p(\mathbf{z}) dz_r dz_i = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z_r \left[ \int_{-\infty}^{\infty} p(\mathbf{z}|\mu) p(\mu) d\mu \right] dz_r dz_i \quad (11)$$

$$\mathbb{E}[z_r] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z_r \left[ \int_{-\infty}^{\infty} \mathcal{N}_{z_r}(a_r(\mu - \hat{\mu}) + b_r, \sigma_r^2) \mathcal{N}_{z_i}(a_i(\mu - \hat{\mu}) + b_i, \sigma_i^2) \mathcal{N}_{\mu}(\mu_{\mu}, \sigma_{\mu}^2) d\mu \right] dz_r dz_i \quad (12)$$

$\int p(z|\mu)p(\mu)$  can probably be calculated analytically using [Bromiley 2003]. The product of three normal distributions is a scaled normal distribution, so after converting  $N_{z_i}$  and  $N_{z_r}$  to distributions in terms of  $\mu$  for the integration, the normal distribution integrates to 1, and the scaling factor comes out as a function of  $z_r$  and  $z_i$ ,  $S_{fgh}(z_r, z_i)$ , for the remaining two integrals. This leaves potentially very difficult numerical integrations at this step.

Gaussian quadrature:

$$\mathbb{E}[z_r] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z_r \left[ \int_{-\infty}^{\infty} p(\mathbf{z}|\mu) p(\mu) d\mu \right] dz_r dz_i \approx \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z_r [\sum_{i=1}^n w_i p(\mathbf{z}|\mu_i) p(\mu_i)] dz_r dz_i \quad (13)$$

### 2.3 Gauss-Hermite Quadrature

Gaussian quadrature:

$$\int_{-\infty}^{\infty} \exp^{-x^2} f(x) dx \approx \sum_{i=1}^N \omega_i f(x_i) \quad (14)$$

Substitution for normal distributions using Gauss-Hermite quadrature:

$$\mathbb{E}[h(y)] = \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right) h(y) dy \quad (15)$$

$h$  is some function of  $y$ , and random variable  $Y$  is normally distributed.

$$x = \frac{y - \mu}{\sqrt{2}\sigma} \Leftrightarrow y = \sqrt{2}\sigma x + \mu \quad (16)$$

$$\mathbb{E}[h(y)] = \int_{-\infty}^{\infty} \frac{1}{\sqrt{\pi}} \exp(-x^2) h(\sqrt{2}\sigma x + \mu) dx \quad (17)$$

$$\mathbb{E}[h(y)] \approx \frac{1}{\sqrt{\pi}} \sum_{i=1}^N \omega_i h(\sqrt{2}\sigma x_i + \mu) \quad (18)$$

### 2.4 Mutual Information Calculation

The signal measurement probability distribution  $p(\mathbf{z})$  can be approximated using Gauss-Hermite quadrature. The calculation is performed separately for the real and imaginary components,  $p(z_r)$  and  $p(z_i)$ , because  $z_r$  and  $z_i$  are assumed independent.

$$p(z_r) = \int p(z_r|\mu) p(\mu) d\mu = \int \frac{1}{\sqrt{2\pi}\sigma_{\mu}} \exp\left(-\frac{(\mu - \bar{\mu})^2}{2\sigma_{\mu}^2}\right) p(z_r|\mu) d\mu \quad (19)$$

$$= \int \frac{1}{\sqrt{\pi}} \exp(-x^2) p(z_r | (\sqrt{2}\sigma_\mu x + \bar{\mu})) dx \approx \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n p(z_r | \sqrt{2}\sigma_\mu x_n + \bar{\mu}) \quad (20)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n p(z_r | \mu_n) \quad (21)$$

An identical calculation for the imaginary component results in

$$p(z_i) = \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n p(z_i | \mu_n) \quad (22)$$

Calculate expectation values for real and imaginary components by definition and approximating  $p(\mathbf{z})$  with Gauss-Hermite quadrature as shown above.

$$\mathbb{E}[z_r] = \int z_r p(z_r) dz_r \approx \int z_r \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n p(z_r | \mu_n) dz_r = \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \int z_r p(z_r | \mu_n) dz_r \quad (23)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathbb{E}[z_r | \mu_n] = \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r(\mu_n) \quad (24)$$

Similarly for the imaginary component,

$$\mathbb{E}[z_i] \approx \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathbb{E}[z_i | \mu_n] = \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_i(\mu_n) \quad (25)$$

The variance can be calculated as follows:

$$\mathbb{E}[(z_r - \mathbb{E}[z_r])^2] = \mathbb{E}[z_r^2] - (\mathbb{E}[z_r])^2 = \int z_r^2 p(z_r) dz_r - (\mathbb{E}[z_r])^2 \quad (26)$$

$$\approx \int z_r^2 \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n p(z_r | \mu_n) dz_r - (\mathbb{E}[z_r])^2 = \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \int z_r^2 p(z_r | \mu_n) dz_r - (\mathbb{E}[z_r])^2 \quad (27)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \int z_r^2 \frac{1}{\sqrt{2\pi}\sigma_\nu} \exp\left(-\frac{(z_r - \mathcal{G}_r(\mu_n))^2}{2\sigma_\nu^2}\right) dz_r - (\mathbb{E}[z_r])^2 \quad (28)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \int (x^2 \sigma_\nu^2 + 2x\sigma_\nu \mathcal{G}_r(\mu_n) + \mathcal{G}_r^2(\mu_n)) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx - (\mathbb{E}[z_r])^2 \quad (29)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n (\sigma_\nu^2 + \mathcal{G}_r^2(\mu_n)) - (\mathbb{E}[z_r])^2 = \frac{\sigma_\nu^2}{\sqrt{\pi}} + \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r^2(\mu_n) - (\mathbb{E}[z_r])^2 \quad (30)$$

Again, an identical calculation for the imaginary component yields

$$\mathbb{E}[(z_i - \mathbb{E}[z_i])^2] = \frac{\sigma_\nu^2}{\sqrt{\pi}} + \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_i^2(\mu_n) - (\mathbb{E}[z_i])^2 \quad (31)$$

The off-diagonal elements of  $\Sigma_z$  are equal.

$$\mathbb{E}[(z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i])] = \mathbb{E}[(z_i - \mathbb{E}[z_i])(z_r - \mathbb{E}[z_r])] \quad (32)$$

$$\mathbb{E}[(z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i])] = \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i]) p(\mathbf{z}) d\mathbf{z} = \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i]) \int p(\mathbf{z}|\mu) p(\mu) d\mathbf{z} d\mu \quad (33)$$

$$\approx \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i]) \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n p(\mathbf{z}|\mu_n) d\mathbf{z} = \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i]) \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n p(z_r|\mu_n) p(z_i|\mu_n) dz_r dz_i \quad (34)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \int (z_r - \mathbb{E}[z_r]) p(z_r|\mu_n) dz_r \int (z_i - \mathbb{E}[z_i]) p(z_i|\mu_n) dz_i \quad (35)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \int (z_r - \mathbb{E}[z_r]) \frac{1}{\sqrt{2\pi}\sigma_\nu} \exp\left(-\frac{(z_r - \mathcal{G}_r(\mu_n))^2}{2\sigma_\nu^2}\right) dz_r \int (z_i - \mathbb{E}[z_i]) \frac{1}{\sqrt{2\pi}\sigma_\nu} \exp\left(-\frac{(z_i - \mathcal{G}_i(\mu_n))^2}{2\sigma_\nu^2}\right) dz_i \quad (36)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \int (\sigma_\nu x + \mathcal{G}_r(\mu_n) - \mathbb{E}[z_r]) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx \int (\sigma_\nu y + \mathcal{G}_i(\mu_n) - \mathbb{E}[z_i]) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{y^2}{2}\right) dy \quad (37)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n ((\mathcal{G}_r(\mu_n) - \mathbb{E}[z_r])(\mathcal{G}_i(\mu_n) - \mathbb{E}[z_i])) = \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n (\mathcal{G}_r(\mu_n) \mathcal{G}_i(\mu_n) - \mathcal{G}_r(\mu_n) \mathbb{E}[z_i] - \mathcal{G}_i(\mu_n) \mathbb{E}[z_r] + \mathbb{E}[z_r] \mathbb{E}[z_i]) \quad (38)$$

$$= \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r(\mu_n) \mathcal{G}_i(\mu_n) - \mathbb{E}[z_r] \mathbb{E}[z_i] \quad (39)$$

$$\Sigma_z = \begin{bmatrix} \frac{\sigma_\nu^2}{\sqrt{\pi}} + \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r^2(\mu_n) - (\mathbb{E}[z_r])^2 & \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r(\mu_n) \mathcal{G}_i(\mu_n) - \mathbb{E}[z_r] \mathbb{E}[z_i] \\ \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r(\mu_n) \mathcal{G}_i(\mu_n) - \mathbb{E}[z_r] \mathbb{E}[z_i] & \frac{\sigma_\nu^2}{\sqrt{\pi}} + \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_i^2(\mu_n) - (\mathbb{E}[z_i])^2 \end{bmatrix} \quad (40)$$

$$|\Sigma_z| = \left( \frac{\sigma_\nu^2}{\sqrt{\pi}} + \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r^2(\mu_n) - (\mathbb{E}[z_r])^2 \right) \left( \frac{\sigma_\nu^2}{\sqrt{\pi}} + \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_i^2(\mu_n) - (\mathbb{E}[z_i])^2 \right) - \left( \frac{1}{\sqrt{\pi}} \sum_{n=1}^N \omega_n \mathcal{G}_r(\mu_n) \mathcal{G}_i(\mu_n) - \mathbb{E}[z_r] \mathbb{E}[z_i] \right)^2 \quad (41)$$

$$I(\mu; z) = H(z) - H(z|\mu) = \frac{1}{2} \ln((2\pi e)^2 \cdot |\Sigma_z|) - \frac{1}{2} \ln((2\pi e)^2 \cdot |\Sigma_\nu|) \quad (42)$$

### 3 Derivations

### 4 Directions